Trader Leverage Use and Social Interaction:
The Performance Implications of Overconfidence and Social Network Participation on Retail Traders

Submitted by John Hall Forman III to the University of Exeter
as a thesis for the degree of
Doctor of Philosophy in Finance
In October 2015

I certify that all material in this thesis which is not my own work has been identified and that no material has previously been submitted and approved for the award of a degree by this or any other University.

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Abstract

Overconfidence and its relationship to investor market participation is well established in the finance literature. The research into investors and social networks is only in its infancy, however. This thesis extends the literature by expanding on both subjects individually, then bringing them together.

Empirical work on individual investors in the existing literature links overconfidence and excess trading, resulting in impaired returns. The preferred activity metric, monthly account turnover, encapsulates two separate elements, though. One is trade frequency. The other is leverage use. Chapter 4 of this thesis theorizes based on the existing literature that in fact trade frequency is not a good measure of overconfidence. It then demonstrates through empirical analysis of a group of individual non-professional foreign exchange traders that leverage is much more suitable to that role.

Chapter 5 turns the focus to social networks, particularly with respect to information transfer. The literature in finance anticipates that network members benefit from their membership. Further, network position (social capital) enhances that benefit. This thesis challenges that expectation with respect to non-professional investors. Findings based on analysis of members of an online retail foreign exchange trader social network indicate that while there may be an educational benefit accruing to unsophisticated members, for more sophisticated ones membership appears to have a negative effect on returns.

One potential explanation for the negative impact of network membership is explored in Chapter 6 in the form of impression management. It is hypothesized that sophisticated investors are influenced in their behaviour by the realization they are being observed, and also the size of their audience. Analysis of foreign exchange traders indicates an increase in leverage use among sophisticated investors as their audience size increases, coinciding with a decline in trade excess returns, making the case for an observation-based rise in overconfidence.

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Acknowledgements

I would like to express my sincere thanks to my supervisors Dr. Constantinos Antoniou and Professor Joanne Horton for their support and guidance through the last three years. Professor Horton in particular was invaluable in the development of Chapters 5 and 6 of this thesis.

I would also like to acknowledge Asaf Yigal, David Karp, Michelle Heath, and Jonathan Jesse for their assistance in obtaining the data used in this thesis and for answering my numerous questions about its collection, processing, structure, and management.

Finally, it is quite likely that I would not have even pursued a PhD without the constant prodding of Professor Gordon Dash Jr. For that and the support he provided along the way, he has my gratitude.

Chapter 1: Introduction

1.1. Motivation and Contributions

The motivation of this thesis is to examine the activity and performance of active traders and the factors which motivate their behaviour and influence their actions and outcomes. In general terms, this text will contribute to the individual investor behavioural literature summarized by Barber and Odean (2013) in several ways. First, it will further the work being done to examine the behaviour of non-professionals operating in a relatively high frequency trading environment (as opposed to the more traditional longer-term investor) and by extension how they can influence prices. Second, it will expand the research into trading in the foreign exchange market, specifically at the retail (individual investor) level, which has thus far only received limited attention because of that market's relatively short period of existence. Third, it will contribute also to the very early-stage finance literature which explores the relationship between social network participation and investor behaviour and returns, particularly with respect to online social networks. All this is achieved by examining three specific areas: leverage and overconfidence, network participation influence on trader performance, and the influence of observability on trader activity.

1.1.1. Leverage and overconfidence

The act of making a trade in the financial markets involves two primary decisions at the time of execution. One is whether to trade long or short based on the outcome of some analytical process by which expectations for future price movement are derived. The other is how large a position to take, which is a function of both the amount of capital available as a constraining factor and the perceived riskiness of the trade. The position size decision can be expressed in terms of leverage, where leverage is simply the ratio of the value of the trade relative to the trader's capital.[1] Since the leverage decision is based on the trader's perception of risk and/or opportunity, it is inherently subject to the influence of overconfidence. While prior research, most notably Barber and Odean (2000), has reflected the relationship between leverage use and

[1] This ratio is generally expressed in market usage as N:1, where N would equal 1 when trade value equals capital. For equity market investors, N is generally less than 1, while for participants in the futures and forex markets N is quite often double digits, or even higher, indicating the taking on of positions many times the value of the underlying capital.

overconfidence-driven investing performance, it has done so in an undifferentiated way. That is to say, leverage thus far has been a factor in the extant literature as part of aggregate measures of trading activity such as turnover, but has mainly not been segregated for analysis in its own right.

The relationship specifically between leverage and overconfidence is explicitly evaluated in Chapter 4. Using retail forex trader data in this regard provides considerable opportunity to do so thanks to the ample leverage allowed in that market, as well as the relatively high trade frequency. While a starting point is to confirm a negative relationship between returns and the level of leverage employed by a trader, which is accomplished employing quintiling methods similar to those of Barber and Odean (2000), this is far from sufficient given the context of a negative-sum market such as retail forex (as documented in Chapter 2). Trading larger positions, just as trading more frequently, all else being equal, will inherently result in more negative returns in a negative expectancy environment. As a result, to properly assess the link between proposed indicators of overconfidence such as leverage use and trade frequency (as the two contributors to turnover) it is necessary to control for the nature of the market in question. Benchmarking techniques have been employed in the prior literature to accomplish this, but they are not available in retail forex. The result is the requirement to analyse performance on a more granular basis at the per trade level. This is accomplished using regression modelling. The results not only support the hypothesis that increased leverage use is indicative of increased overconfidence, even when factoring for overconfidence influencing factors such as experience and investor sophistication, but also that leverage is a better indication of overconfidence than is transactional frequency.

The findings of Chapter 4 extend the research into overconfidence and trading activity, therefore, in a number of ways. First, it expands it into a market which has not, thus far played much of a part in the research because of its relative newness and limitations on data availability. Second, it brings leverage to the fore as an important indicator of overconfident trading behaviour. Third, it shows how overconfident trading does not simply impair performance because of the impact of added trading costs, but in fact results in worse trades being executed. All of this is accomplished while controlling for elements such as trader experience and sophistication which should impact on an individual's tendency toward overconfident trading.

1.1.2. Network participation influence on trader performance

Do traders actually benefit from being connected with other traders and exchanging information with them? The literature developed thus far presents a mixed picture. There is evidence in support of the idea that being part of a network, and in particularly being a well-positioned member of said network, can be highly beneficial (Ozsoylev et al., 2011, Horton et al., 2012). Those results tend to presuppose the existence of private fundamental information in the network, however. In the context of a network comprised almost entirely of retail traders or investors, it is highly questionable whether such information is present. This is particularly true in the case of a market where a small number of instruments are traded and fundamental (valuation-determining) information is both readily available and slow-changing.

That said, non-fundamental private information may be found in a network which could provide a benefit to its members – for example, education or sentiment. Analysis of a network of traders participating in the kind of market which features highly public, infrequently changing fundamentals and a limited number of tradable instruments would offer the opportunity to make an evaluation exclusionary of the influence of private fundamental information. This is the motivating factor behind Chapter 5, which explores the information transmission idea from the perspective of retail foreign exchange traders.

One cannot evaluate information transmission without also considering the influence of the context in which that transmission takes place and the impact that may have on those involved. The literature has thus far only begun trying to answer related questions. For example, the likes of Hong et al. (2004) suggest that being social plays a part in determining how active a given trader or investor is as a market participant. To the extent that excess trading could be linked to overconfidence (Odean, 1999), the implication is that aspects of being a part of a social network could have an impact on returns. Finally, the literature suggests that being part of a network could tend to alter one's views and/or behaviours, which certainly has the potential to play a meaningful role in trader performance.

The way information receipt drives potential behaviour changes amongst those participating in a social network is addressed in Chapter 5. It is accomplished by examining key metrics of trading activity to see the degree to which they change based on network membership and one's position in the network. This then provides a basis for at least starting to understand the driving factors behind the changes in returns seen after traders join the network. The findings presented point to a strong positive influence from the network for those in a position to gain educational benefits, but at the same time a strong negative (presumably social) influence on performance for those individuals for whom education is not a major consideration. Interestingly, in the latter case the potentially explanatory factors of socially driven increased trade frequency, information driven overconfidence, and/or network motivated changes in risk aversion prove not to be explanatory.

Chapter 5 thus extends the literature in multiple ways. First, it expands the fledgling use of actual (as opposed to hypothetical) social network data in finance, in particular as it relates to the online space, and continues to explore the idea of social capital. Second, it extends the literature related to the transmission of information between and amongst investors, particularly where it relates to high frequency market participants. Third, it expands the research in the area of the linkage between social interaction and investor behaviour. Fourth, it expands the consideration of heterogeneity with respect to the performance and behaviour of traders and investors. Fifth, it further develops the research into potential herding behaviour and peer effects.

1.1.3. The influence of observability on trader activity

Are investors influenced by having others watch them participate in the markets? The psychology research would suggest that is probably the case. The finance literature has explored this subject to a limited degree, mainly looking at it from the perspective of what one shares with others on a filtered, voluntary basis. What if the information is not filtered, though? What if an investor had an audience watching every trade they make? The psychology literature makes a good case for some sort of behavioural impact as the investor looks to influence the way they appear to others.

Chapter 6 explores the idea of observer effects on investors by examining members of a retail foreign exchange social network. The particular network in question offers a somewhat unique structure whereby members are able to see each other's trading activity in virtual real time with no filtering. That provides the opportunity to ascertain whether having others watch them alters an investor's decision-making. The areas of risk aversion, trade disposition, overconfidence, and market timing alternation are all examined in this context. The findings point to negative audience size effects with regards to overconfidence and market timing, with potentially broader effects in the areas of disposition and risk aversion.

The findings presented in Chapter 6 extend the literature by developing the concepts of observer effects and impression management with respect to finance. It also furthers the research into financial social networks and their influence on members and member performance. Additionally, it extends the behavioural finance literature with respect to the topics of overconfidence and trade disposition.

1.1.4. The study group and data source

Central to the analysis described above is the dataset employed throughout this thesis. It comes from a retail (individual) foreign exchange trader online social network. While equity market investor studies are quite common in the finance literature, the same cannot be said for participants in the forex market. Studying retail forex traders in particular allows for both extending prior studies of equity market investors in a new direction and the examining a group of market participants who are fairly homogeneous as mainly speculators and who tend to operate in a high frequency manner. As documented in Chapter 2, the retail forex market has a somewhat unique position within the overall market structure. This offers some interesting research opportunities, both in terms of high frequency actors and looking at activities which have a limited impact on market prices.

The fact that the data under consideration comes from a social network makes it novel with respect to the finance literature. Social network analysis is beginning to make inroads in the research. This dataset directly links network participation with transactional activity and returns, as documented in Chapter 3, allowing for the merging of some of the key areas of research in behavioural finance with social considerations within a network context.

1.2. Thesis Structure

The structure of this thesis is as follows. Chapter 2 provides a description of the retail foreign exchange market – its structure, mechanics, and participants. Retail foreign exchange – as differentiated from inter-bank or futures market foreign exchange trading - is the primary focus of the empirical work presented in subsequent chapters. Chapter 3 follows with a definition and description of the dataset used in the research herein, a relatively novel dataset which comes from a retail forex trader social network. Chapters 4, 5, and 6 are the primary research chapters. Chapter 7 concludes, notes some important caveats, and presents considerations for future work.

Chapter 2: The Retail Spot Forex Market Structure and Participants

2.1. Introduction

The structure of the institutional foreign exchange (forex) market is well documented, with King et al. (2012) providing a recent summation of its current state. It is a market dominated by an over-the-counter (OTC) inter-bank system whereby exchange rates are determined in a decentralized multiple-dealer structure, with the spot market as the driving force, though not necessarily representing the largest volume sector (Lyons, 2001).

What is less well documented is the retail (individual investor) spot forex market. This is unsurprising since until only relatively recently it was virtually non-existent. Retail forex trading has only been active in earnest since around the year 2000 (King et al., 2012), facilitated by the development of online trading platforms made available by retail aggregators,[2] which allow for smaller minimum transaction sizes than commonly traded in the inter-bank and futures markets.[3] Previously, the retail segment was considered too small to be economically interesting by banks (BIS, 2013).

Through the aggregators, the retail market also has a decentralized multiple-dealer structure in a fashion similar to the inter-bank market, with an array of institutions providing pricing and transactional capacity. The difference, however, is that the aggregators are largely price takers. Those using a dealer model may simply pass along inter-bank spot prices received from liquidity providers (generally inter-bank dealers), perhaps with a spread mark-up (King and Rime, 2010). Those using a pure broker model merely provide access to an electronic communication network (ECN) where orders are matched in an exchange-like system. The ECN model is the less frequently applied of the two. That said, however, it must be noted that aggregators do not necessarily operate in a single-model fashion. For a number of reasons (redundancy of

[2] Retail aggregators are commonly referred to in the market as brokers, though there is actually a mixture of dealer and broker models employed.
[3] The online platforms also no doubt contributed to more active trading, as per the findings of Barber and Odean (2001).

systems, risk management, etc.) any given aggregator may operate multiple models side-by-side.[4]

On the surface, therefore, the retail spot forex market looks rather like the institutional spot market in that it features a number of price-making entities servicing a larger group of price-taking ones, with Figure 2.1 providing a basic indication of the relationship between the different parties. This belies the fact, however, that much of the exchange rate pricing in the retail market is simply passed down from the inter-bank arena. The retail forex structure is thus effectively a step removed from the inter-bank market. As a result, it is not a meaningful price discovery mechanism.

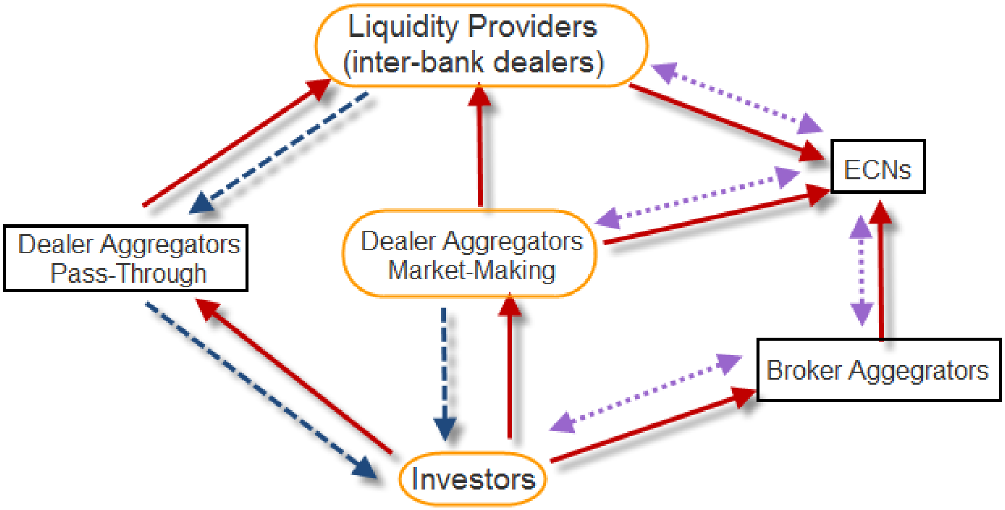

Figure 2.1 – The primary parties in the retail forex market
Those who hold, or may hold, net positions appear in rounded boxes, while non-position-holding entities are in rectangles. Solid arrows indicate the direction of order flow. Single direction dotted arrows indicate the direction of price dissemination, indicating price-maker/taker relationships. Double-direction arrows indicate two-way price flow.

It must be noted, however, that in the retail spot forex market there is no actual exchange of currencies. This will be explained in Section 2.3, but some of the implications are important to address here as this structure has led to accusations of the aggregators acting like so-called “bucket shops”. If applying the Raines and Leathers (1994) description of bucket shops as being places where no buying or selling takes place, but rather both sides merely pretend to do so with an obligation to pay based on price changes (making them a form of derivatives market), then there is justification for such characterizations. This

[4] The workings of one particular retail forex aggregator are described in Nolte & Nolte (2011)

assessment is made by the numerous accusations of fraudulent practices – both anecdotal and regulator-initiated – aimed at aggregators over the years.[5]

With this in mind, the retail aggregators are now much more regulated than the inter-bank players in that countries have begun developing and enforcing rules and guidelines[6] as a consumer protection mechanism, with the US and Japan leading the way (King and Rime, 2010, King et al., 2012). This serves to blunt the bucket shop accusations, at least in terms of the more dubious aggregator activities. Though in some parts of the world the regulation of retail forex remains limited or non-existent, in recent years the overall impression is one of a more controlled and transparent environment – much less "Wild West".

Despite the concerns about aggregators acting like bucket shops, retail participation in forex nevertheless is an example of rapid growth since its inception. Galati et al. (2007) note that Japanese investors alone were indicated by one source to have grown from under 2,000 accounts at the start of 2003 to nearly 120,000 in 2007,[7] and a survey of five of the largest global retail aggregators indicated that daily traded volumes rose over 300% from 2007 to 2010 (King and Rime, 2010). The latter suggests long trading hours, liquidity, low transaction costs, and the availability of high levels of leverage as being the main drivers of increased retail participation in the forex market. The ability to trade readily from both the long and short side and low initial capital requirements were both additionally noted in survey results (CitiFX, 2010a).

Investor discontent with the equity market, which during the observed period was going through many upheavals (bear markets, corporate scandals, etc.), is likely to be an undocumented contributing factor as well. This is not to suggest, however, that retail spot forex trading can be viewed as a substitute for long-term stock market investing (particularly that related to personal retirement accounts and similar structures). As will be shown, retail forex is primarily a short-term speculator market. That suggests any transition to it from stocks predominantly comprises equity investors operating in similar time frames, with similar objectives.

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[5] The Forex Peace Army website is a place where many of the former can be found – http://www.forexpeacearmy.com/public/forex_broker_reviews.

[6] Margin requirements, standard accounting methods, minimum aggregator capital levels, price slippage fairness, etc.

[7] According to Rime and Schrimpf (2013), Japan has a 36% share of retail spot forex volume, more than the next two markets (US and UK) combined.

Forex Magnates estimates that in 2011 daily volume among retail investors was $217bln per day (Magnates, 2011), which compares to an estimate from 2010 of $125bln-$150bln from King and Rime (2010) based on that year's Bank for International Settlements triennial survey (BIS, 2010). Indicative of how elusive good volume figures are in this decentralized market, however, Segal (2012b) estimates daily volume in April 2012 as $172bln, with limited (if any) real growth in activity since 2010 when volumes were suggested to have seen their highest monthly reading. Forex Magnates supports the flattening volume trend during that period, with steadily declining volume in Japan over the previous two years contributory to the levelling pattern (Magnates, 2012). This corresponds with the number of active trading accounts among the US retail aggregators reporting to the Commodity Futures Trading Commission (CFTC) holding fairly steady between Q2 2010 and Q2 2012, as reported in Greenberg (2010) and Greenberg (2012a) respectively.

There was concern that increased regulation, changing market dynamics, and/or simple maturation of the markets may have led to a stabilization in retail forex volumes, but they expanded once more in 2013. The 2013 BIS volume survey (BIS, 2014) indicates a continuation in the general uptrend in overall foreign exchange volumes, seeing the average daily turnover crossing the $5trln level. Segal (2013) reports that estimates of the June 2013 retail volume averaged $329bln daily, indicated as an all-time record which was subsequently extended to $360bln in October 2014 (LeapRate, 2015). This figure actually matches, or even exceeds, the total daily trading volume of the global equity markets noted by Rime and Schrimpf (2013). Additionally, there is a modest uptick in the number of active US trading accounts in 2013 over 2012 based on the quarterly aggregator reporting referenced above (Greenberg, 2012a, Greenberg, 2012b, Greenberg, 2012c, Finberg, 2013a, Finberg, 2013b, Greenberg, 2013, Siddiqui, 2013, Finberg, 2014).

2.2. Linking Retail Forex to the Inter-Bank Market

The involvement of liquidity providers in offering pricing and transactional capacity to the retail aggregators links the retail spot forex market with the broader currency market, as those providers are mainly inter-bank dealers. Without them, retail forex would effectively be a self-contained construct – a kind of virtual market (as per the bucket shop discussion above). In many ways that remains largely the case in as much as individual investor positions are matched against either each other or against dealer aggregators.

There are investor position imbalances, however, where retail traders are collectively either net long or short a given currency pair. Historical net position figures published by OANDA (2012), shown in Figure 2.2, provide a sampling from one of the largest global aggregators (Magnates, 2012), which likely means it can be assumed to be fairly representative of the patterns in the market as a whole. FXCM, the largest global retail aggregator, publishes similar positioning figures via its DailyFX unit,[8] which also documents such imbalances. It is, in fact, rare that customer positions actually balance out, and at times the imbalances can be quite substantial. This implies the existence in the retail forex system of one or more institutions holding a net position which offsets the aggregate individual investor imbalance. To a certain degree, that is handled by those aggregators acting in market-making dealer roles, at least within the constraints of their risk management policies.

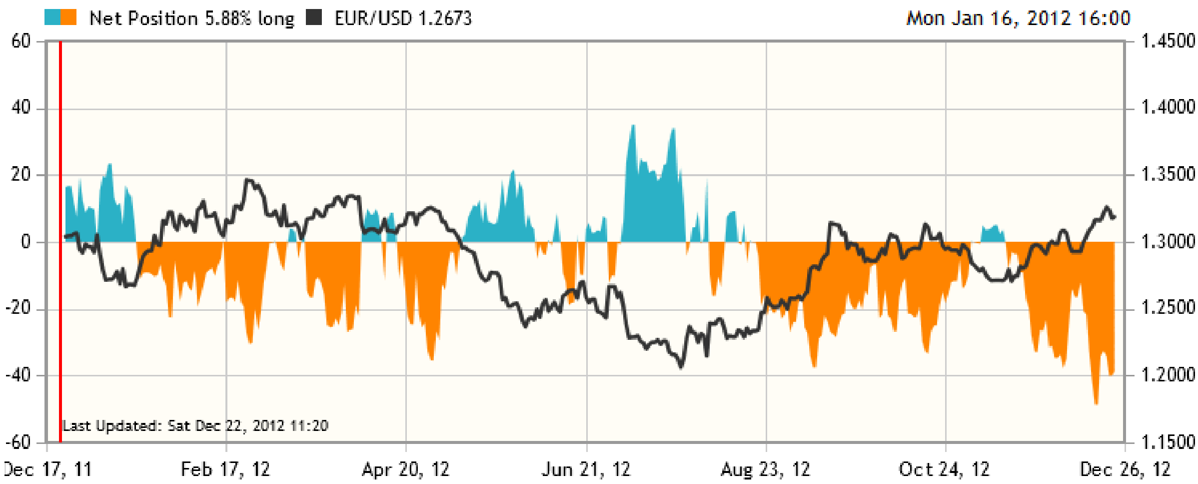

Figure 2.2 – Net Positions in EUR/USD Over a 12-month Period
One year of net investor positions in EUR/USD with an overlay of the EUR/USD exchange rate (black line). The histogram values are determined by subtracting short positions from long positions. For example, if there were 60% longs and 40% shorts, the reading would be 20. Source - OANDA

The liquidity providers are the institutions at the end of the retail imbalance chain. Through the orders passed directly to them by the

[8] http://www.dailyfx.com/technical_analysis/sentiment

dealer/broker aggregators, they have immediate exposure to the imbalances which develop. This is furthered by any hedging capacity they provide to the market-making aggregators. To the extent that these imbalances are not handled through internalization, which is something noted as broadly increasing by King et al. (2012) and suggested by Rime and Schrimpf (2013) as potentially being as high as 75%-85%, it is then expected that they offset them externally. [9]

This liquidity provider internalization motivates questions as to how much of an impact the noted retail imbalances have on the inter-bank market. The OANDA net position figures show a nearly 50% short imbalance for EUR/USD on December 15, 2012 (see Figure 2.2). That translates to 25% long positions set against 75% shorts. There are no published figures regarding total retail spot forex open position volume like the Commitment of Traders report published weekly by the CFTC,[10] so it is hard to know what a 50% imbalance means in those terms. One can get some basic idea of potential exchange rate market impact by looking at the retail forex volume, though.

The latest BIS (2014) survey figures indicate average daily inter-bank spot market turnover of approximately $2.0trln. If the $329bln per day Segal June 2013 estimate is used, then a 50% overall order imbalance coming out of the retail market in net supply/demand on a given day would represent about 8% of total daily inter-bank market turnover. Of course the 50% imbalance is on the extreme end of readings and comes from only a single currency pair, so one would expect to see smaller imbalances for the retail market taken as a whole. Rime and Schrimpf (2013) suggest that retail trading accounts for only 3.8% of spot market turnover in terms of the flows which actually reach the bank dealer level. The rest are internalized by liquidity providers, as well as lower down the channel in the retail platforms.[11] This implies a limited impact on exchange rates at the inter-bank level, counter to the conclusions drawn by Barber et al. (2009b) and Barber et al. (2009c) that retail order imbalances create a noise trader effect of pushing prices too far.[12] Further, liquidity providers largely view retail investors as uninformed, so are generally more willing to hold their net

[9] While the liquidity providers cannot create exact contract offsets outside the retail market because of the non-deliverable nature of retail forex contracts, they can reasonably hedge externally any exchange rate exposure which develops.
[10] http://www.cftc.gov/marketreports/commitmentsoftraders/index.htm
[11] Rime and Schrimpf (2013) indicate that internalization rates vary considerably by currency pair, but are unlikely to exceed 50% (GBP/USD indicated as 15%-20% as an example).
[12] Which is not to say noise trading among institutional level market participants cannot do exactly that.

positions in inventory (King et al., 2012) than perhaps would be the case with institutional counterparties, assuming they are not internalized against inter-bank customer flows.

That said, large imbalances in some of the less liquid currency pairs and imbalances hitting at times when general market liquidity is low could see retail flows exert a short-term influence on exchange rates. This is particularly true in the case of a “hot potato” effect among inter-bank dealers (Lyons, 1997).[13] Further, to the extent that liquidity providers are able to ascertain which group(s) of retail investors are informed - providing them with a kind of private information, as suggested by Lyons (2001) - they will be less inclined to hold their inventory and more likely to attempt to quickly offset their exposure to such players externally. Thus, even as uninformed or noise traders (Black, 1986), retail forex investors may have some impact on exchange rates as suggested by Long et al. (1990) and Kogan et al. (2006).

2.3. Retail Spot Forex Trading Mechanics

While nominally called a spot market, retail forex operates differently than the inter-bank spot version. The latter involves transactions in which the exchange of one currency for another is set to occur on a settlement date in the near future (1-2 business days) at a specific exchange rate. It is functionally very like a short-dated forward contract. Unless a later agreement offsets this transaction, the two parties will do the agreed upon exchange, at the designated rate, when the appointed day and time arrives.

No exchange of currency ever takes place in the retail forex market. This is not to say, however, that retail spot forex is a cash-settled futures or non-deliverable forward (NDF) market, though it can be viewed very similarly to both in certain ways, as will be shown below.

A retail spot forex transaction starts in a manner similar to one in the inter-bank market with an agreement to do a future exchange. There is never any settlement, however. Instead, at the end of each trading day - assuming no offsetting intervening transaction - the agreement is automatically rolled forward

[13] Rime and Schrimpf (2013) suggest that structural changes in the global foreign exchange market mean dealers are no longer necessarily at the centre of “hot potato” trading, but that such trading through non-dealer market makers continue to influence exchange rates.

to the next available settlement date.[14] The result is that these quasi-forward contracts are perpetual, with no expiration or delivery date.

Since there is no exchange of currency, retail spot forex trading is completely focused on the movement of exchange rates. These are quoted in the same standard XXX/YYY fashion as seen in the inter-bank market whereby XXX is 3-letter ISO 4217 (a.k.a. SWIFT) code for the base currency, and YYY is similarly the code for the quote currency. The reading of these exchange rates is that one unit of the base currency is worth N units of the quote currency. For example, EUR/USD is the exchange rate between the euro and the US dollar, where the former is the base and the latter the quote. Thus, a reading of 1.2000 for EUR/USD would indicate €1 as being worth $1.20.

When entering into a retail spot forex position, as in the case of futures and NDFs, the investor posts margin equivalent to some fraction of the value of the transaction. For example, US aggregators registered with the National Futures Association (NFA) and/or CFTC must require the posting of at least 2% in initial margin, depending on which currencies are involved (more in the case of lower-liquidity pairs). This is not a down payment on a loan for the purchase of an asset, unlike margin deposits in the stock market. Rather it is a deposit to reduce the aggregator's credit risk in the case of customer losses from adverse exchange rate movements, as in the futures market.

Also similar to the case of the futures market, positions in retail spot forex are subject to mark-to-market accounting. This is done in real time on a continuous basis, which allows for a wrinkle in the margin call mechanism. When an investor's account equity (cash minus open position losses) falls below the required maintenance margin level, rather than issuing a request for additional funds, as is the traditional case in the futures and equity markets, the aggregator in most cases simply closes out the investor's position(s) with immediate effect. This takes place no matter when during the trading day it happens. These automatic forced closures further reduce the aggregator's credit risk, and actually serve to prevent the investor from going into a negative equity situation in all but the most extreme situations.[15] The result is the ability

[14] Global aggregators commonly use 16:00 or 17:00 New York time as the end of the trading day, but some more regional ones operate on a schedule appropriate to their primary time zone.
[15] The January 2015 move by the Swiss National Bank to no longer support the EUR/CHF exchange rate was one such extreme event. The resulting volatility not only resulted in trader

of the aggregator to provide greater leverage to the investor than would otherwise have been prudent.[16]

2.4. Retail Forex as a Zero-sum game

Because retail forex is based on obligations rather than asset transfers – agreements to do a future exchange of currency, albeit ones which never actually happen – it means there must be opposing long and short sides to all open positions. Where a retail aggregator acts in a dealer fashion it is nominally the counter-party to all customer positions, with the aggregator hedging positional imbalances externally as per its risk management policies. Where the aggregator operates in a broker fashion, while legally it may still be official counter-party, the effective counter-party will be external - a liquidity provider, another aggregator, the customer of another aggregator matched via an ECN, or some combination thereof.

Regardless of the aggregator model, for each customer long there must either be a customer or an institution short on the other side somewhere in the market, and vice versa. That means every change in exchange rates is at once financially benefitting one party and harming another by the same amount. This is reflected in the following profitability functions for the two counterparties to the transaction:

$$L = P_T - P_0 \tag{2.1}$$

$$S = P_0 - P_T \tag{2.2}$$

where

L is the gain/loss for the long

S is the gain/loss for the short

P_0 is the spot exchange rate at time *t*=0 (trade entry point)

P_T is the spot exchange rate at time *T* (trade close or other profit measurement point)

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losses, but also significant broker ones. See http://www.wsj.com/articles/switzerland-scraps-currency-cap-1421320531.

[16] Before the initiation of a cap of 50:1 leverage in the US, 100:1 leverage and higher was commonly available. That remains the case today in much of the world. Japan and South Korea are exceptions as leverage regulations there have become even stricter than in the US (Segal, 2012a).

The above functions work equally for either point-based or currency-denominated profit/loss calculations. In the latter case, one would simply multiply through by the number of base currency units to get a change in value in quote currency terms.

Since the P_0 and P_T terms above offset, there is a simple zero-sum structure to each position:

$$L + S = 0 \tag{2.3}$$

By way of example, say Investor A expects EUR/USD to appreciate from its current rate of 1.20 and wants to go long 100,000 euros against the dollar. To do so, someone (Investor B) must be found who is willing to go long 120,000 dollars against the euro (100,000 x $1.20). The transaction being done, Investor A will benefit from a rise in EUR/USD to the detriment of Investor B, and vice versa in the case of a fall. If EUR/USD rises to 1.30, the 100,000 euros is worth $130,000 - a $10,000 gain for Investor A and a $10,000 loss for Investor B. The gains and losses net out. No wealth is ever gained or lost, just transferred between investors.

2.5. Retail Forex as a Negative-sum game

Like all traded markets, retail spot forex features bid-ask pricing. All transactions done whereby the aggregator is acting as dealer puts the customer in a price-taker position (buy at the offer, sell at the bid), as do all those where the aggregator is merely passing through prices from a liquidity provider. In the case where the aggregator passes customer orders through to an ECN for order matching there is the prospect for the customer to be a price-maker through the use of limit orders, but all market orders will put the customer in a price-taker position. As a result, the majority of transactions see the customer on the wrong side of the bid-ask spread. An adjustment therefore needs to be made to Equations 2.1 and 2.2 to reflect bid-offer pricing:

$$L = P_{b,T} - P_{o,0} \tag{2.4}$$

$$S = P_{b,0} - P_{o,T} \tag{2.5}$$

where

$P_{b,0}$ and $P_{o,0}$ are respectively the bid and offer spot exchange rates at time *t*=0

$P_{b,T}$ and $P_{o,T}$ are respectively the bid and offer spot exchange rates at time *T*

It is worth noting that now the situation is such that both the long and short could lose. This would occur if the market failed to move sufficiently for one side to overcome the bid-offer spread. That can be demonstrated by imagining the case where a position is opened and immediately closed before the market could move. The long would have entered at the offer price and exited at the bid price, while the short would have entered at the bid and exited at the offer. In this case both would lose the bid-offer spread, so *L* + *S* = 2(P_{b0}-P_{o0}).

The change to account for bid-offer pricing means the Equation 2.3 equivalency no longer holds. It must be adjusted as follows, with the addition of the term C to account for any commissions paid:

$$L + S = \left(P_{b,T} - P_{o,0}\right) + \left(P_{b,0} - P_{o,T}\right) - C \qquad (2.6)$$

The result of accounting for the bid-offer spread and any commissions or other fees levied by aggregators is a negative-sum market for the aggregate of investors. The market as a whole remains zero-sum, so there must be a positive side offsetting the negative investor side. This is the liquidity providers and market-making aggregators who are on the right side of the spread (and collecting any commissions).

To get some idea of just how much money is shifted out of retail investor accounts and into the hands of those institutions through the bid-ask spread, an estimate can be derived. The most actively traded currency pair is EUR/USD (BIS, 2010). As a result it has a very tight spread that is often just about 1 pip (King et al., 2012), which equates to 1/10,000 of a US dollar. At an exchange rate of 1.3000 for EUR/USD the spread is worth about 0.008% of the value of a transaction. Using the $329bln June 2013 average daily volume estimate noted above, and multiplying that spread value through, the result is a bid-ask cost estimate of about $26.3 million per day. This, of course, is actually an unrealistically low estimate as the spread for other currency pairs is not as narrow as the one for EUR/USD.

There's an additional element which needs to be included for a full understanding of how much of a negative-sum game retail forex trading is in aggregate for investors (and, conversely, positive for the liquidity providers and aggregators). From the perspective of profitability and risk exposure, a retail spot forex transaction functions as if one borrows a given currency, exchanges it for another, and invests the proceeds, then reverses the process when the trade is closed.[17] More specifically, it is as if the long side has borrowed the quote currency and invested an equivalent amount of the base currency (based on the exchange rate at position entry), and vice versa for the short. Thus, an investor's profitability is the gain/loss on the exchange rate change, less any commission paid, plus the net cumulative difference between the interest earned and the interest paid. The latter is the so-called interest carry. It is paid or received (depending on which side of the spread one falls) at the end of each day when the spot position is rolled forward to the next settlement date. [18]

Thus, the investor profitability functions for each side look like this:

$$L = (P_T - P_0) - C + \sum_{d=0}^{n} (i_{b,d} P_d - i_{q,d}) \tag{2.7}$$

$$S = (P_0 - P_T) - C + \sum_{d=0}^{n} (i_{q,d} - i_{b,d} P_d) \tag{2.8}$$

where

P_d is the spot exchange rate at the rollover of day *d* (*n* being the number of days held)

$i_{b,d}$ is the 1-day overnight interest rate of the base currency at rollover of day *d*

$i_{q,d}$ is the 1-day overnight interest rate of the quote currency at rollover of day *d*

[17] This doesn't actually happen, but the accounting for gains, losses, and interest rate differentials accruing to the holder of a position operates as if it does.

[18] The manner by which aggregators deal with interest carry varies. There is even at least one broker who employs continuous carry such that it is not just positions held beyond the end of the trading day which earn/pay the interest differential.

Notice that P_d is used to convert the interest on the base currency to quote currency terms. This normalizes the total carry interest into quote currency terms to match the rest of the equation.

For example, someone going long EUR/USD has a return function equal to one where they borrow dollars overnight, convert them into euros at the current spot rate, then invest the euros overnight. Such an investor is then subject to both exchange rate movement and the spread in the overnight interest rates between the euro and the dollar.

The result of this structure is that interest carry accrued while holding a retail spot forex position will approximate the premium/discount priced into a forward contract of equivalent time to delivery (assuming covered interest parity). The difference is that the interest rate differential will be debited to, or credited from, the investor's account daily when holding a spot position, whereas in the forward that income/loss will come as a narrowing in the basis as the contract approaches delivery.

This can be expressed for a long position (in terms of the base currency in a pair) as:

$$F_0 - P_0 \cong \sum_{d=0}^{n} (i_{b,d} P_d - i_{q,d}) \tag{2.9}$$

where

F_0 is the forward exchange rate at time *t*=0

Substituting the forward price equation for F_0 produces:

$$P_0 \frac{(1 + r_{b,0})}{(1 + r_{q,0})} - P_0 \cong \sum_{d=0}^{n} (i_{b,d} P_d - i_{q,d}) \tag{2.10}$$

Or in the case of a short position:

$$P_0 - P_0 \frac{(1 + r_b)}{(1 + r_q)} \cong \sum_{d=0}^{n} (i_{q,d} - i_{b,d} P_d) \tag{2.11}$$

where

$r_{b,0}$ is the n-period interest rate of the base currency at time *t*=0

$r_{q,0}$ is the n-period interest rate of the quote currency at time *t*=0

Because the left side of the equation features a ratio for the interest differential whereas the right side features a summation, the two sides of the equation do not quite equate, even when the *i* and *r* rates are equivalent. For example, if spot EUR/USD is currently 1.2000 with the 1-yr EUR and USD rates are 2% and 1% respectively, it would mean a 1-yr forward rate of 1.2119 (1.2 x 1.02/1.01 = 1.2119), resulting in an interest differential (basis) return of 0.0119 if one were to go short the forward against a non-interest bearing long cash EUR position. By comparison, if EUR/USD held constant at 1.2000 through the full year, one would see a 0.0140 cumulative interest carry return (0.02 x 1.2 – 0.01) on a long retail spot position. What creates the potential for a greater or smaller disequilibrium is the fact that the *r* rates in Equations 2.10 and 2.11 are fixed while the *i* rates are variable (as is P_d).

Bringing the long and short sides of the retail spot forex position together, the total net interest carry (N) can be expressed in this fashion:

$$N = \sum_{d=0}^{n} (i_{b,o,d} P_d - i_{q,b,d}) + \sum_{d=0}^{n} (i_{q,o,d} - i_{b,b,d} P_d) \tag{2.12}$$

where

$i_{b,b,d}$ and $i_{b,o,d}$ are the bid and offer overnight rates respectively for the base currency at rollover on day *d*

$i_{q,b,d}$ and $i_{q,o,d}$ are the bid and offer overnight rates respectively for the quote currency at rollover on day *d*

The bid-ask granularity on the overnight interest rates in Equation 2.12 is required because aside from expressing the reality of the markets, it also facilitates understanding of how carry interest is not zero-sum, as perhaps would be expected. Since $i_{b,o,d} < i_{b,b,d}$ and $i_{q,o,d} < i_{q,b,d}$ (bid interest rates being higher than offered rates), the amount earned on the long currency of each side is less than that paid on each short side. Thus, *N* will always be negative.

Moreover, it is possible for both the long and short to experience negative interest carry. This would come about if the interest rates of the two currencies are sufficiently close together or the bid-offer spreads sufficiently wide to create a situation where the offer rate on the long currency is lower than the bid rate on the short currency, or vice versa.

Adding in the carry interest, the full expression of the net cumulative return of a retail forex position becomes:

$$L + S = (P_{b,T} - P_{o,0}) + (P_{b,0} - P_{o,T}) - C + \sum_{d=0}^{n} (i_{b,o,d}P_d - i_{q,b,d}) + \sum_{d=0}^{n} (i_{q,o,d} - i_{b,b,d}P_d) \tag{2.13}$$

The bottom line is that the retail spot forex market is negative sum for investors after factoring in exchange rate spreads, overnight interest rate spreads, and the commissions charged by some aggregators. This necessarily has implications for participation in the market since on average investors are expected to have negative returns.

2.6. Participants in the Retail Spot Forex Market

The survey done by CitiFX (CitiFX, 2010a, CitiFX, 2010b) mentioned above provides some information as to the make-up and motivation of the population of participants in the retail spot forex market. The CitiFX survey may not strictly be confined to retail spot forex market participants, especially since about 6% of respondents indicate having at least 10 years of experience (meaning longer than retail spot forex had been readily tradable), but the respondents are likely to be mainly from that sector, so the results can be taken to be fairly indicative (nearly 80% indicated five or fewer years of forex experience).

Just under 91% of respondents describe themselves as individual non-professionals, and just shy of 83% listed speculation as their main reason for trading currencies. About 9% say hedging is their primary focus.[19] That hedging figure may be a bit misrepresented, however, as the term has taken on a somewhat different meaning in retail forex. This requires some explanation.

In normal parlance, hedging is generally meant to indicate putting on a position in a related security to offset all or part of some aspect of risk inherent in a primary position. For example, a long-only equity sector fund portfolio manager could short index futures as a hedge against systematic risk. This at least significantly reduces the exposure of said portfolio to a market decline,

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[19] The remainder selected “other” but details as to what that entails are not included in the survey results.

while leaving the portfolio exposed to the residual idiosyncratic risks of the sector and individual stocks held.

In retail forex trading, hedging has a more extreme connotation. It has come to mean putting on opposing positions in the same currency pair. For example, if one were long 100,000 EUR/USD, a hedge in this usage of the term would entail going short 100,000 EUR/USD (or one could do a partial hedge by going short something less than 100,000 units). By any normal definition this would be considered an offsetting transaction which closes one's position (no residual risk of any kind). Some aggregators do not force net accounting, however, so investors are able to have such opposing positions show as simultaneously open in their accounts.[20]

In 2009, the National Futures Association (NFA) introduced a new ruling which prohibits US member aggregators from employing this so-called hedge accounting, requiring both net and first-in, first-out (FIFO) accounting (NFA, 2009). The NFA regulation only applies to registered aggregators operating in the US. Those operating outside the US remain free to offer hedge accounting.

The CitiFX survey indicates 25.9% of respondents usually trade using hedging in this definition of the term. Anecdotal evidence indicates some of these investors actually consider this offset version of hedging to be a strategy rather than just an accounting variation as it should be properly viewed. This may mean the aforementioned 9% who describe themselves as being hedgers is an overstatement due to confusion as to the definition of the term. Such a conclusion tends to be supported by the fact that only 8.7% of respondents indicate position holding periods longer than a few days (43.3% indicate generally holding for a few hours or less), which is the time horizon in which one would expect to see traditional hedgers operate. As a result, it is probably safe to say more than 83% of individual investors can be classified as speculators.

In any case, hedgers are not likely to be as active as speculators (in terms of frequency of transactions) given their generally longer time horizons and less frequent transactional requirements. As a result, one would expect the ratio of speculative activity to hedging activity in terms of at least number of trades, and probably dollar-equivalent volume as well, to be higher than the ratio of speculative investors to hedgers reported by the survey.

[20] Even in cases where aggregators use net accounting (as currently required in the US), traders can circumvent it by using multiple accounts, or sub-accounts.

Supporting that case, King et al. (2012) includes a table of survey results which incorporates information from five of the largest global retail aggregators. They are indicated has having a mean of nearly 1.2 million transactions per day, each averaging about $61,000 in notional value. The five taken together account for about half the King and Rime (2010) estimated daily volume, which suggests the total number of daily transactions in the retail spot forex market could approach 2.5 million. By comparison, the survey shows average trade notional value of just over $2mln for the ten institutional trading platforms surveyed. Applying that to the $1.5trln BIS spot volume figure for that period (BIS, 2010) results in an estimate of roughly 750,000 transactions per day done at the institutional spot level. This means individual investors trade, on average, 3-4 times as often as institutions lending strong support to the notion that retail investors are primarily speculators.

On the question of returns, only 26.8% of respondents indicate a negative return in the prior 12 months. The numbers reported to the CFTC by US aggregators do not corroborate this figure as they indicate only about 30% of active investor accounts (meaning accounts where at least one transaction was made) in any given quarter show a profit (Greenberg, 2010, Greenberg, 2013). It is a major stretch to suggest US investors underperform those from the rest of the world so badly as to close that gap, especially when over 20% of the survey participants report being from the US.[21]

Nearly 40% of respondents indicate they consider themselves full-time traders, yet only 29.7% of them indicate trading more than 15 hours per week. Most said they only trade forex, but about 37% note being active in multiple markets, with over 70% of the latter group listing equities as one of their secondary choices, and 47% listing commodities.

In terms of their approach to trading exchange rates, a total of 89.2% of respondents indicate they use strategies employing technical analysis, with 36.1% saying they do so exclusively. Only 8.1% say they employ strictly fundamental analysis. This bias fits with the strong leaning toward short-term trading, as slower changing fundamentals favour longer-term strategies. The prevalence of technical analysis based strategies and the short time frames in

[21] The figures reported quarterly to the CFTC actually are not far off the profitability percentages reported in Jordon and Diltz (2003).

which they operate makes a good case for classifying retail forex market investors as largely being noise traders per the Black (1986) definition.

Furthering the strategy discussion, the evidence seems to point toward the application of mean-reversion (counter-trend) oriented approaches. This can be seen in Figure 2.2, taken from the previously referenced OANDA historical position ratios. Notice in the figure how investors were consistently positioned against the prevailing direction of the exchange rate. They tended to be net short when EUR/USD was rising and net long when it was falling. This is something which lends support to the earlier-noted view that individual investors as a collective are uninformed noise traders, matching the findings of Bloomfield et al. (2009a), though without the potential price impact the authors identify.

2.7. An Adversarial Game

Treynor (1999) uses the term adversarial to describe the relationship between the two parties in a securities transaction when two criteria are met. The first is a zero-sum financial relationship in that one party to the transaction will end up better off than the other because either one of the exchanged assets (cash or stock in the case of the equity market) will outperform the other, or both will move comparably. The second is that both sides are playing to win, meaning they are seeking to profit rather than just managing cash positions. The argument is that the cash management operations will largely offset, leaving the dominant institutional trading to be adversarial.

Looking at retail forex from Treynor's perspective, one can see an even more acute adversarial relationship between players. At least in an asset market it is possible for both of the exchanged assets to rise in value, increasing wealth for both parties (even as one may outperform). In a negative-sum market like retail forex it is impossible for both parties to come out ahead financially (though, as noted in Section 2.5, it is theoretically possible for them to both lose money).

To assess the second of Treynor's criteria the prospective counterparties for an investor position – another investor, an aggregator, or a liquidity provider (or multiples and combinations thereof) – must be reviewed. As discussed earlier in Section 2.2, investor positions will net out to a degree, making them effective counterparties for each other, and that group largely comprises profit-seeking speculators, as the above survey results indicate. To the extent that investor positions don't fully offset, institutions will be on the other side of the imbalance. Because liquidity providers (and likely market-making dealer model aggregators as well) view the aggregate of retail investors as uninformed, as previously discussed, they view positions taken in opposition to said investors as having a positive expected return. Thus, institutional counterparties are profit-seeking as well.

By Treynor's definition then, retail forex must be viewed as being highly adversarial. It is zero-sum in nature and the vast majority of counterparties are profit-seeking. If this is accepted, then the conclusion must be that above average skill is required to earn any kind of positive return. A merely average investor would have a negative expected return after factoring in the previously outlined exchange rate and carry interest bid-offer spreads and any commission costs. The more informed investors will tend to take money away from the less informed ones over time. It is very much like poker where there is a random element to any singular outcome, but in the long run money will flow out of the pockets of the less-skilled players into the pockets of the more-skilled ones (with the house taking a small cut). This contrasts with a market like equities where one can earn positive returns with a passive (index, etc.) strategy, which requires little skill and likely will result in outperformance over many active managers.

2.8. What Makes Them Think They Can Win?

The question which one cannot help asking at this point is why investors take part in retail spot forex trading at all given that taken collectively they will lose money, as highlighted above. Since that negative-sum nature is akin to casino games, there is the automatic inclination to ascribe a gambling mentality to forex participation. There are certainly grounds for doing so.

Kumar (2009b) demonstrates that individual gambling preferences are reflected in equity investment decisions, resulting in a disproportionate focus on stocks with lottery characteristics. The high levels of leverage allowed retail forex investors[22] may facilitate similar behaviour among retail forex investors since it provides considerable opportunity for entering positions with asymmetric

[22] The CitiFX survey results show nearly half admit to employing 50:1 or greater leverage.

return profiles. Further, Kumar indicates an increase in gambling type investment behaviour during troubled economic times, which could be an uncited factor in the growth of retail forex in the 2000s when there were considerable economic and socio-political upheavals.

Gambling investors cannot be the only market participants, however. If all investor positions offset such that there is no need for a dealer to hold an imbalanced book, then perhaps a case could be made for an all-gambler market, but it can be observed in the OANDA positioning data referenced above this isn't the case. And because all longs require matching shorts, there must be someone on the other side of those imbalances. If gambling investors are viewed collectively as underperformers in terms of having negative expected returns, then there must be informed investors with positive expected returns on the other side of the gambler net position. As noted, the liquidity providers and market-making aggregators willing to hold unbalanced books can be viewed as being informed investors. The question is to what extent there are other informed investors outside of those institutional ranks.

There are no extant figures to offer a clear answer to that question. The best available is the previously noted profitability figures reported by US aggregators to the CFTC. While those reports indicate that about 30% of active accounts are profitable in any given quarter, they do not indicate returns, nor is there information on how many of the same accounts are profitable across quarters. The latter would provide an indication of persistence in performance, potentially indicative of the presence of informed investors. The only conclusion which can be drawn is that most retail forex investors lose money.

That brings the discussion to the third group of retail forex market participants – non-gambler investors who enter the market believing they have the skill required to profit, or that they can acquire it through education and experience. To put it another way, they believe they are informed, or can become informed.[23] At any given time, then, there is a group of market participants either working toward becoming informed investors or working toward the realization that they are not informed investors and/or will not become informed investors. Mahani and Bernhardt (2007) and Linnainmaa

[23] Of course those with a gambling mentality may also think of themselves in this way, and those who no longer have gambling as a primary motivation but continue to trade the market would end up in this third category.

(2011) address investors in this category of “learning” investor, as is discussed in Chapter 4 with regards to its impact on how actively they trade. This then motivates the question as to how reliable are investor assessments of their level of informational advantage and/or their ability to develop such an advantage, which speaks to the degree of overconfidence which exists among retail forex traders.

The first element of being or becoming an informed investor is actually understanding the structure and mechanisms of the market. This includes the realization that the market is adversarial and thus requires one to not just be informed, but to be more informed than average to be profitable. Only after that comes being informed in the nature of exchange rate forecasting, etc.

The indications are that even the most basic of functional understanding among investors is lacking. Highlighting this is the example of the NFA legislation against so-called hedge accounting mentioned previously. The regulator specifically cites a lack of knowledge among investors in a letter to the CFTC (Sexton, 2008) as one of the justifications for requiring that aggregators employ net and FIFO accounting. To quote:

> “*The other trading practice NFA believes must be addressed involves a strategy that FDMs refer to as ‘hedging’, where customers take long and short positions in the same currency pair in the same account. NFA is concerned that customers employing this strategy do not understand either the lack of economic benefit or the financial costs involved.*” [24]

Supporting the NFA concern about the lack of understanding among investors is the sometimes vehement reaction expressed when the new regulation was announced. The lengthy comment section of Forman (2009) offers examples of both the anger (evidenced by some fairly explicit language) and the clear lack of knowledge among investors (especially when more than 25% of them report holding these sorts of offsetting positions per the CitiFX survey). Some even indicated their belief that their success in generating

[24] FDM=Forex Dealer Member.

positive returns is due to this “hedging” (the NFA using the term “*strategy*” in the quote above supports this case), which obviously is a case of misattribution.

In other words, before even getting to the point of investors overestimating their ability to consistently profit from anticipating/forecasting exchange rate movements there is evidence of overconfidence in terms of fundamental market understanding. Ironically, the 30% profitability figure noted above may only exacerbate the problem by creating a misunderstanding among investors as to the percentage of profitable investors there are in the retail forex market. The CFTC initiated reporting of this data in 2010 to increase transparency. In doing so, however, to the extent investors fail to realize there may not be a high degree of persistence in accounts profiting from quarter to quarter, they may have made matters worse rather than better.

2.9. Trade Replication Programmes

In recent years there has been a move toward what is referred to as copy, auto, or social trading, with that trend seen continuing Magnates (2012). These systems are ones whereby the trades done by one investor are automatically replicated in one or more other investor accounts. In this way investors are provided the opportunity to have all or part of their account effectively traded by someone else (presumably an informed trader). Some are specifically managed – and even regulated in some cases. Others are much more open-access in nature.

This is not the same as one investor managing multiple accounts, however, which is something which has been around in the markets for many years. In this case the initiating investor has no actual control over the linked accounts. Instead, there is an intermediate automated system which observes when trades are initiated, then duplicates those trades (the specific processes and compensation structures at work among the competing systems vary).

For example, Investor A goes long EUR/USD. The copy-trading platform sees this action. It then initiates new long positions in the accounts of Investors B, C, and D such that now all four accounts are holding the same position as outlined in Figure 2.3 (though likely with variations in relative size of position based on a number of considerations). When Investor A closes the long trade, the platform will close all the other trades as well. The intention is that Investors

B, C, and D have accounts (or portions of them) which replicate the performance of Investor A.

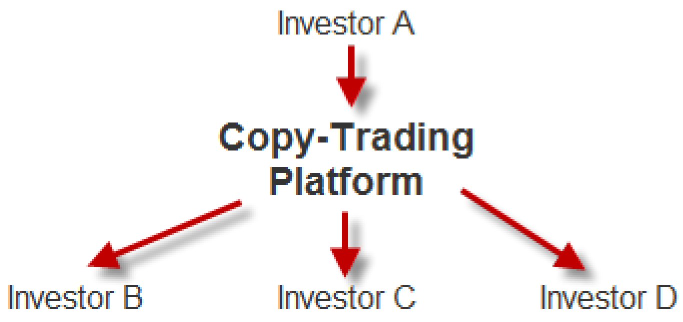


Figure 2.3 – Structure of a Copy-Trading Platform
Trades done by Investor A duplicated in the accounts of Investors B, C, and D.

On the face of it, the potential growth of such systems suggests the increased influence of informed traders in the retail forex market – assuming those whose trades are being duplicated are in fact mostly informed. This implies the market could become more competitive at the individual investor level. It could also mean liquidity providers are less inclined to take the other side of retail investor position imbalances, which creates the potential for greater influence of retail on the inter-bank spot market prices. For these sorts of things to happen in a meaningful fashion, though, copy-trading will likely have to grow faster than the overall rate of growth of the retail market to allow for its influence to expand as a ratio of trading activity.

Even if copy-trading does grow its market share, there are some factors which could limit its influence on competitiveness and exchange rates. One comes from the fact that investors retain control over their account though the copy-trading process when another investor's trades are being replicated. As such, they can close trades (all or part) prior to them being closed by the initiator, no doubt with influence from the disposition effect (Shefrin and Statman, 1985). To the extent they do so, they reduce the impact of the presumably informed investors they are following, while also reducing their own returns.

The other factor potentially working against copy-trading having a large influence is that in most cases an investor can opt into and out of copy-trade relationships whenever they like, rather like moving in and out of mutual fund investments. As a result, effects on investor performance from poor selection decisions and “timing” which are akin to those seen in equity mutual fund research, such as that of Friesen and Sapp (2007) may result.[25]

2.10. Research Potential

The retail spot forex market, because of its structure and composition, offers a unique research opportunity. Unlike other markets, which comprise of participants with a variety of different purposes for taking part (issuance, hedging, cash management, fiscal/monetary policy, etc.), retail forex is almost exclusively a realm of speculative activity. As such, it offers a window into speculative behaviour across all markets otherwise not available because of the heterogeneity of transactional intent in other places. Through it researchers may be able to extend ideas developed in the considerable literature regarding equity investor behaviour. The retail spot market may not (at least currently) have much impact on exchange rates in the inter-bank market because of its fairly insular nature, but the analysis of its participants’ behaviour could very well have a significant impact on what is known about the impact of speculative activity on financial markets more broadly.

[25] The authors find that market timing by investors reduces average returns.

Chapter 3: The Data

3.1. Introduction

The primary data set used for the analysis in this thesis is an expanded version of the one used by Simon and Heimer (2014), Heimer (2013), and Simon (2013). It comprises transactional, positional, performance, and limited demographic information from a retail foreign exchange trader social network. This network followed the definition of Boyd and Ellison (2007) in that it allowed for the creation of a member profile (using screen names rather than real names), the connection with other members, and the ability to view their connections. The network in question was formed in early 2009 (earliest completed registration was February 2, 2009) as the first of its kind for individual retail forex traders, although it was in limited testing until October of that year when it was opened to the public. It should be noted that although the initial period was private, there was no defined selection process involved in recruiting members. To quote one of the co-founders in a comment to me, "*We invited anyone with a pulse that trust us enough to give us his credentials while we were still unknown*."

Participation in the social network required members to link the platform to their live brokerage account.[26] This granted the platform the ability to collect data from those linked accounts - to include transactions executed, orders entered, and positions held – both by capturing all activity moving forward from registration and by collecting historical transaction information available in the account.[27] It was strictly a read-only configuration. The platform could not execute trades or enter orders, unless a given member took part in an available trade duplication program addressed in Section 3.2 below, which is a separate research consideration. Members had no control over which actions and/or transactions done in their broker account were exposed to the platform.[28]

From the perspective of representing the transactional record of a large group of traders, the data in question is comparable in general terms to the

[26] Only real-money trading accounts were permitted. No demo, practice, or paper trading accounts were allowed.
[27] There was historical data collection only for some of the membership either due to technical limitations or the simple lack of any data to collect (new trader and/or new account).
[28] It should be noted that the social network in question was closed down in 2014 after being acquired by one of the large global retail aggregators.

types of equity market datasets used previously in the research (Odean, 1999, Barber and Odean, 2000, Grinblatt and Keloharju, 2001, Garvey and Murphy, 2005, Dorn et al., 2008, Grinblatt and Keloharju, 2009, Linnainmaa, 2011, Grinblatt et al., 2012, Kelley and Tetlock, 2012, Barber et al., 2013), though obviously has a global breadth of coverage rather than single-market one as in most cases. From the perspective of retail forex, it is similar to the data used by Nolte and Voev (2011). Their dataset, however, only includes data from a single broker covering a single month worth of trading, albeit with more traders involved. The dataset used for this thesis includes data from a broad number of brokers, as addressed below in Section 3.4. With pre-registration historical transactional activity included, it covers the period from July 2008 to early May 2013 for a total 58 full months, and one partial.

Because the dataset includes traders from all across the globe, as highlighted in section 3.3, and because some brokers allow customers to open accounts in something other than their native currency,[29] the accounts included are denominated in a number of different currencies. In order to standardize for analysis, all non-USD values for trade volumes and nominal gains/losses (part of the transactions record described in Section 3.5), along with account balances (part of the data described in Section 3.6) have been converted to USD using the requisite closing exchange rate of the day in question.[30]

3.2. Trade Duplication Service

A feature of the social network in question was the ability of members to follow the trades of selected other members. As documented in Chapter 2 (Section 2.9), this was done via a mechanism which replicated the trades done by a given "leader" in the accounts of one or more "followers" for the purposes of trying to match the performance, all of which was handled by the network as intermediary.[31] The leaders were compensated on a performance basis, earning a percentage of the profits they generated for their followers in a system which was similar to that used by hedge funds. Leaders were initially recruited from amongst the social network population, with the network managers scanning through performance records for potential candidates. Over time, however, the

[29] For example, a UK trader having a USD-denominated account rather than one based in GBP.
[30] Daily closing exchange rates were collected from Thomson Reuters for this purpose.
[31] This required a separate set of legal permissioning by the member to allow the network to execute trades in their account.

inclusion of new leaders in the program took on a more professional aspect, with some leaders actually not being individuals, but rather trading shops.

This functionality and participation of members in the social trading mechanism means there are a number of duplicated (follow) trades in the transactional records. The inclusion of these follow trades means the dataset features both trades which were initiated by the member themselves (self-directed) and those initiated by a second party. Heimer and Simon (Heimer, 2013, Heimer, 2014b, Simon, 2013, Simon and Heimer, 2014) avoid dealing with this particular issue by working only with data from before the trade duplication system was implemented. Since the follow trades introduced into a member's transactional record actions and performance which cannot be specifically attributed to them, as well as essentially duplicate trades into the aggregate, only self-directed trades are included in this study. Conceptually, this brings the data in line with the motivation of Barber and Odean (2000) in terms of looking to avoid direct external influence on trading performance.

The exclusion of these follow trades creates a split dynamic to the two primary parts of the data set. On the one hand, excluding positions indicated as initiated as part of the duplication service from the transactional record outlined in Section 3.5 below is fairly straightforward. They are tagged in the record, so easily filtered out. Unfortunately, the daily performance record, which is the second primary part of the dataset (described in Section 3.6), is not so easily handled. It is required that any period in which follow trades took place be excluded to avoid having returns which are not fully based on self-directed trading activity.

While analysis of the leaders would be a very worthwhile pursuit in its own right, unfortunately the dataset lacks indications of when a leader started and stopped in that status. As a result, analysis of behavioural changes, which are the subject of Chapters 5 and 6 with respect to the network members, cannot be performed based on leadership status change.

3.3. The Traders

Between February 2009, when the social network started accepting members, and May 2013 over 49,000 registrations were made to join. Of those, 11,931 actually went on to link their brokerage account to the network. Of that group 7,180 had trading activity recorded which was self-directed (not exclusively followed trades). Figure 3.1 shows the growth in registered active members for the network from inception through the end of the dataset, with Figure 3.2 indicating the number of members with at least one trade in any given month. A rapid expansion period during 2010 can be observed during which time the network was aggressively marketed to new members. Those efforts were curtailed thereafter, shifting to a focus on the trade duplication service. The network continued to grow steadily thereafter, but the combination of the shift in direction and general attrition saw a steady downside progression in the number of members actively trading in their own right each month.

The dataset includes a limited amount of demographic data provided primarily through the user completing a profile during the registration process. Not surprisingly, given the social network is a primarily English-language platform (and the company behind it was based in the United States), the vast majority of members have English as their primary language. This can be observed in Figure 3.3. As can be seen in Figure 3.4, though, the members come from all over the globe, with Europe actually representing the largest fraction at just over a third.

Technical analysis dominates the trading styles indicated by members as their preferred. Figure 3.5 shows the distribution of styles, with technicals representing nearly two thirds and fundamental analysis coming in at only 4%. This fits well with the indicated trading frequency of the members. As can be seen in Figure 3.6, about 57% of them claim to trade 6 or more times per week. Those engaged in primarily fundamentally driven trading would not be expected to be nearly so active.[32]

Members of the network are relatively inexperienced, as indicated in Table 3.7. Those in the 1-3 year range of indicated history in the markets represent the largest fraction. Add in those indicating 1 year or less of experience, and it covers about two thirds of the community. If one makes the reasonable assumption that these experience values are not changed later in most cases, then they provide an indication of experience at the time traders joined the network. The suggestion, therefore, is that the network mainly attracted newer traders, which has implications for its value to the membership.

[32] It must be noted that these trade frequencies are member-indicated values, not actual ones based on their transactional record.

This distribution is in line with the distribution seen in the CitiFX survey results discussed in the last chapter.

As well as capturing member trading activity and performance, the network also presented that information on its platform via each user’s viewable profile page. Members were given a choice of privacy setting for sharing this information. At the most relaxed level, members could opt to either make their data fully viewable within the network and even beyond to the public. Alternatively, they could opt to only allow their “friends” to view their activity, or to not allow it to be seen at all. Figure 3.8 shows the distribution of choices. Only a small fraction actually chose one of the more restrictive privacy options.

The final demographic element is age. As can be seen in Figure 3.9, membership in the network is biased toward the younger end of the adult age spectrum. At the time individuals joined the network they averaged about 37 years old. The 25%-75% range is 28 to 43, so this is not a playground for retirees. Given the relative youth of the retail forex market, the inexperience of the membership, and the bias toward highly active styles of trading noted above, the relative youthfulness of the traders in question probably should come as no surprise. It must be noted that the age data is very messy, however. Values are missing in a large percentage of cases and even when present there are numerous clearly erroneous values. The reliability is so questionable that age values are not included in the analysis which follows in Chapters 4 through 6 where demographic information is included. They are presented here for rough indicative purposes only.

An additional aspect of the data worth mentioning comes from the biography part of the available profile information. A quick scan of these entries written by members offers at least some information on the motivation of traders to join the network. The indicated drivers toward membership are diverse. They included clear commercial interests such as members promoting their trading-based websites. Given the involvement of certain members as leaders in the trade duplication service noted in Section 3.2 above, this is to be expected. Some members were clearly motivated on educational grounds, while still others express a desire to connect with fellow traders. Unfortunately, a detailed analysis of these biographical offerings is beyond the scope of this thesis, though it would certainly seem to present a research opportunity.

3.4. The Brokers

Approximately 70 different retail foreign exchange brokers (aggregators) have members included in the social network data set. Table 3.1 provides a listing of the top 20 by number of accounts included. Some of the brokers, such as OANDA and FXCM, are global operators, while others are regionally focused. The permissions and technical linkages required to allow the network to access customer accounts were developed at different points, resulting in a progressive expansion of the number of brokers included over time. The reporting and data extraction methodologies employed by the brokers, and between them and the social network, have some variation. This variation contributed to inconsistencies, and in some cases errors, in the resulting dataset, which had to be addressed in preparing it for use. These are addressed in sections 3.5 and 3.6 below.

The total number of brokerage accounts linked to the social network is indicated at over 19,000. This is considerably more than the number of members who completed their registration, as noted above in section 3.3, which is a result of the network allowing members to link in multiple accounts, either from the same broker or from different ones. Approximately 76% of members have only 1 account. Another 13% have two accounts linked to the network. About 3.5% of members have more than 5 linked accounts. The largest indicated number of accounts for one member is 95.

It should be noted that sub-accounts with a given broker are considered different accounts, at least in some cases.[33] Sub-accounts can be used by traders to operate in multiple account base currencies in some cases (for example, having a GBP sub-account when the main account is denominated in USD). They can also be used to segregate by trading methodology or some other differentiating factor.

The implication of varied account currencies is discussed in Section 3.9.

3.5. The Transactions

Half of the core of the dataset is a transactional record containing all pertinent details regarding each round-turn trade executed. Trades still showing

[33] I am aware that OANDA sub-accounts function in this fashion, but do not know if this is the case with other brokers as well.

as being open, which is an extremely small fraction, are excluded to both ensure the exclusion of potentially erroneous entries and to provide actualized returns for analysis. Trade records showing errors in entry such as lack of volume, open date/time listed as falling after the closing date/time, missing prices, etc. are also excluded. When filtering out the follow trades described in Section 3.2 above, the total transaction count is just over 4 million, representing $194.6 billion in transactional volume. This works out to an average trade volume of about $48,600, which is 20% less than the average trade size noted in Chapter 2 (Section 2.6). Long trades represent 49% of the number of transactions and 48% of the total volume.

Table 3.2 provides descriptive statistics for trade volumes, holding period, and returns. The volume and holding periods are both quite heterogeneous, with considerable skewness reflective of the diversity of the size and style of the traders included in the dataset. The fact that most trades are quite small (less than $10,000 in notional value) provides a good indication of the general bias toward smaller traders in the social network. With 75% of trades being held for about 9 hours or fewer, the influence of high frequency (day) traders is clear, though that does not necessarily provide an indication of the distribution of trading time frames among the members.

The average trade has a return of -0.02% in terms of the exchange rate move captured. Given the overall negative sum nature of retail forex trading, as documented in Chapter 2, one would expect to see just such a small average trade loss reflective of the bid/ask spread. The very small frequency of gains or losses in excess of 1% is reflective of both the scale of the moves in exchange rates and the bias toward high frequency trading.

Table 3.3 documents the distribution of currencies traded by the social network members. The top two currencies are predictably USD and EUR. Volume in USD for the dataset, at just over 40%, is quite close to the proportion of overall spot market volume indicated in the BIS (2014) survey results. The proportion of volume in EUR is significantly higher for the network members, however, at 34% vs. 18%. The representation of the other currencies is then relatively lower in the dataset. The only difference in ranking among the major currencies is GBP coming in third and JPY fourth in among member trades, while that is reversed in the BIS figures.

Table 3.4 shows the top 20 most traded exchange rate pairs. The relatively high amount of trades done in EUR noted above is reflected in the dominance of EUR/USD as a trading vehicle for members of the network. The ranking of pairs by trading activity is fairly close to the “favourite” ranking from CitiFX (2010a). Just over half of surveyed traders consider EUR/USD their top choice pair. The social network activity is either side of that, depending on whether one looks at things in terms of number of trades or volume. The fact that it is 60% of volume, but only 40% of trades suggests a bias toward EUR/USD by larger traders, likely because of the high global liquidity and the resulting very narrow bid/ask spread.

3.6. The Daily Returns

The other main part of the dataset is a daily account summary table, which includes the return on the day, account balance, and related information. Unlike the transactions log, the data in this table is largely calculated by the social network at the end of each day. As a result, there is more opportunity for errors. For example, a number of negative account balances were discovered which looked to be a function of a faulty pre-membership historical data retrieval process in certain cases.[34] Such entries are excluded, along with other obvious error cases (such as NULL entries for daily net ROI). Truncation is further applied to entries where the daily net ROI reading is in the most extreme 0.5% readings in both tails so as to drop highly suspect values. When further filtering out days during which follow trades were held, the total number of observations came in at just over 4.3 million.

Table 3.5 provides descriptive statistics for both account balance and daily return values. The account balance figures from Panel A very much support the idea that members of the social network are biased toward being small traders, with less than 5% of observations at $43,000 or higher. Again, considerable skewness is observed. The extremely low values for part of the dataset likely is at least partly a function of accounts denominated in other currencies, such as JPY, being converted in to USD, as mentioned in Section 3.1 above.

[34] This was discussed with administrators of the network, and corrected on their end moving forward, but nothing could be done about the existing data.

Panel B from Table 3.5 provides an indication of the range of daily returns for the traders in the network.[35] In this case, days with a zero return were excluded as most were a function of non-market related account changes such as interest income earned on the account balance and other factors unrelated to having an active position. Average daily returns come in at -0.53%, though it must be noted that this is based on active traded days, not on total available trading days.[36] A comparison of these return values to those from Table 3.2 helps in the appreciation of the influence of leverage on trading performance among retail forex traders, as noted in Chapter 2.

3.7. The Social Network

Connecting with other members is, of course, the point of a social network. Across all members, over 41,000 two-way "friend" links are shown as of early May 2013, with 5,901 members having at least one friend at that point. Unfortunately, the records do not indicate when such links were made, or which member was the initiating party. A second set of friend links from April 2012 is also part of the dataset (5,608 members with at least 1 connection at that date, 5,546 members with at least one connection at both the April 2012 and May 2013 measurement points), so there are potentially two fixed points of observation for any given individual, depending on their membership tenure. As such, there does not exist a time series of friend linkages as members connect with each other, just two discreet measurement points.

Once two members became friends they could see each other's trading activity, within the privacy setting constraints noted in Section 3.3. Figure 3.10 shows two of the aspects of the social network's platform which allowed members to observe what their friends were doing in real time. They could see the orders entered, as well as the positions entered and exited. By clicking through to a friend's profile page, they could then also see overall performance for that individual. It should be noted, however, that friends could not observe each other's position size or capital balance.

[35] It should be noted that these daily return values are inclusive of any interest carry income/expense, though given the short time frames of most trades that is likely a negligible factor.
[36] In other words, a trader may only actually trade 10 days in a month. In such a case, the average daily return would be based on those 10 days, not on the full average 22 monthly trading days (exclusive of weekends).

Table 3.6 provides descriptive statistics for the distribution of the number of friends had by connected members based on the May 2013 data. The median value is 6, with 25% of members having 2 or fewer. Two members have in excess of 1,000 connections, with the upper 1% coming at 128 and above. This helped push the mean number of friends up to 14. Once more the outcome is a high skewed heterogeneous set of data.

While private messaging between friends was a feature of the social network platform, one need not be friends with another member to interact with them. There was a forum area where members could have open discussions. Plus, at a macro level the platform included an indication of the current balance of open positions for the aggregate of members – a sort of real-time version of the Commitment of Traders report from the futures market which can be used to gauge trader sentiment. Figure 3.11 provides a sample.

3.8. Overall Performance

In Chapter 2 the negative sum nature of retail forex is documented. The traders in the social network certainly do not break that pattern. In aggregate their trades come out as a loss of $2.22 per round-turn, inclusive of transaction costs (spread). This is a number which actually sounds pretty reasonable when compared to trading in other markets where commissions can be considerably higher. In fact, the comparison of this figure to spread costs is positive. Based on the average $48,600 in trades size noted in section 3.5, a very low end estimate of spreads would be about $3.75.[37] On this cumulative basis then, the members of the social network are beating the spread, which puts them ahead of the trading curve.

A second measure of performance also provides evidence that members of the social network were, on average, stronger performers than the general population of traders. The quarterly profitability rate the CFTC requires US brokers to post provide a basis for comparison. The performance of network members is compared to the broker figures in Table 3.7. On average across the 14 quarters for which the broker-reported figures are available, just under 31% of accounts were profitable. The compares with almost 39% of the social network accounts, and there are no quarters in which the network membership

[37] This is based on commonly seen 1 pip EUR/USD spread assuming an exchange rate of 1.30, so 0.0001/1.30 = 0.008%.

did worse than the broker figures. Even when only including members indicating the United States as their location, the average for the network is over 35% profitable accounts per quarter and only in Q1 of 2011 is the network profitability rate lower than that reported in the aggregated broker data.

Although the traders in the network collectively show better than average performance, they are not without their predictable flaws. For example, there is support for the influence of the disposition effect on the network membership. The average holding period for winning trades is 1.08 days, with a mean return of 0.19%. In contrast, the average holding period for losing trades is 1.98 days, with a mean return of -0.39%. Clearly, members struggle to hold on to winning trades and exit losing ones quickly.

Additionally, a deeper examination of the figures suggests that the aggregate profitability numbers are biased by the presence of larger traders who likely are better. This can be seen by removing trade size from the equation. When simply looking at the change in exchange rate captured, the average result is a loss of 0.021%. To get an approximation of trade costs, a sample of exchange bid/ask rate spreads was taken, which can be seen in Figures 3.12 and 3.13.[38] The average of those spread costs is 0.015%, which means the average trade does not actually beat the spread. In fact, it is 0.006% worse, which works out to about $2.92 per trade based on the $48,600 average volume.

The bottom line is that the social network members collectively lost nearly $9 million over about a five year period. There are 49,803 trader-month observations in the dataset, where a trader-month is a single month of activity for one member. Members of the network are therefore losing about $180 per active month of trading.

3.9. Calculating Member Returns

As indicated in Section 3.6, the dataset includes daily return values. In keeping with the main part of the related literature, monthly time frames are the primary focus of the research in the next three chapters when considering period returns. Calculating monthly returns from the daily data is a simple function of sequentially multiplying the net ROI values for each active trading

[38] The OANDA spreads, as more specifically representative of those likely to be experienced by retail traders, were given priority, with the Thomson Reuters spreads used to fill in any gaps.

day during the period in question to achieve a compounded return for the month as a whole. As is noted in Section 3.4, some members of the network have multiple trading accounts linked to the network. For the purposes of the research which follows, it is felt that the best indication of individual performance is to combine the returns of the separate accounts of members with more than one into a single monthly value. This is accomplished by weighting the returns of each active account by the USD-equivalent balance and taking an average on that basis.

In theory, only including active accounts in the weighting could result in an understatement of trading capital exposure and a resulting inflation of returns (positive or negative) if traders are actually trading in one account (or a sub-set of their accounts) on the basis of the capital they have across all accounts. The working assumption, however, is that traders will have made trading decisions based on the capital in the account(s) they are trading, not on others they might have. Further, if the inclusion of non-active accounts is deemed desirable then the logical question is to ask why not include all of the individual's assets as the capital basis. Since the focus here is on speculative activity, it makes sense to focus on the capital a trader would view as immediately at risk.

A weighted averaging of returns across multiple accounts of course requires a common currency basis for the account balances. As noted in Section 3.1, a conversion of all account balances in the data is accomplished using prevailing exchange rates. This could only be managed where there is an indication in the account information regarding the currency denomination. Not all accounts have such an indication. An assumption that the accounts are in USD could be made, but some of the notional balance values are so high as to make that an unlikely prospect. Since having USD-equivalent account balances is also critical in the development of the turnover and leverage values used throughout the research which follows, those accounts are excluded. When that is done and the returns are combined with activity derived from the transaction log, the total number of usable members is 5502. This is the group that is the basis for the research to come.

To summarize:

Total member registrations: >49,000
Members who linked their live trading account: 11,931
Members with recorded trading activity: 7,180
Members with usable aggregated returns data: 5,502

3.10. Conclusion

The outline of the dataset provided herein is meant to only offer a general indication of the common backdrop for the research presented in this thesis. That said, there are a couple broad aspects to the data worth discussing.

Firstly, it should be noted that while the transactions collected by the social network were executed in live money accounts, and they represent an unfiltered listing of each member's trades for accounts linked to the network, they cannot necessarily be seen as completely unbiased. While it is true that members could not pick and choose which trades were reported, they could have maintained unlinked accounts which would not be included in the data set. For example, a member may have an unused account linked to the network to gain access, but actually do their primary trading via an unlinked account. There is no way of knowing for sure from the data the degree to which this sort of activity takes place or by which members, though the members with linked account in which no trading activity was ever captured at least offer in indication.

Secondly, survivorship must be viewed as a factor for consideration with this dataset. The downward trend in active monthly members in Figure 3.2, and the quarterly one from Table 3.7, especially in the face of rising overall membership, makes it clear that traders are falling out, either because they have stopped trading or because they have shifted to accounts not tied into the network. Aggregate figures have been presented here to provide a general picture of the dataset, but making major conclusions from them become problematic because of the survivorship issue.

That said, the description of the data provided in this chapter is meant primarily to provide a picture of the dataset given its relative novelty to the literature - not to provide a basis for analysis at this point. In the chapters following, the data is segmented in ways relevant to the research questions being explored, the specifics of which are detailed therein.

Table 3.1
Top 20 Retail Forex Brokers with Accounts Linked in to the Foreign Exchange Trader Social Network

Distribution of member accounts by primary retail foreign exchange broker (aggregator). Where brokers were listed under multiple codes, reflecting different versions of their platform, numbers were combined in to one value. Members of the social network are permitted to link multiple accounts to the network.

Broker	Accounts
OANDA	4,149
FXCM	3,800
FXDD	1,604
Alpari	1,290
IBFX	885
AvaFX	741
Gain	734
FXOpen	686
FxPro	338
ILQ	324
MBTrading	296
Markets.com	262
AdmiralMarkets	244
LiteForex	161
Instaforex	93
GoMarkets	84
Forexyard	82
Tadawul	80
CitiFX	74
Pepperstone	67
All Others	3,405
Total:	19,399

Table 3.2

Distribution of Trade Volumes, Holding Periods, and Returns

Distribution of transaction volumes, trading holding periods, and trade returns of more than 4 million trades done by member accounts by primary retail foreign exchange broker (aggregator). Panel A volumes are in USD. Panel B periods are days and fractions thereof. The Panel C returns are based on the exchange rate move captured, not the actual realized return which would factor in leverage.

Panel A: Trade Volumes

Observations:	4,001,339
25%	1,288
Median	4,000
75%	15,085
Mean:	48,640
Standard Deviation:	1,717,037
Skewness:	205.62

Panel B: Trade Holding Periods

Observations:	4,001,339
25%	0.011
Median	0.062
75%	0.381
Mean:	1.533
Standard Deviation:	12.015
Skewness:	25.059

Panel C: Trade Returns

Observations:	4,001,339
25%	-0.00074
Median	0.00029
75%	0.00121
Mean:	-0.00021
Standard Deviation:	0.00735
Skewness:	-6.51410

Table 3.3
Currencies Traded by Members of the Social Network

Distribution of trade frequency and volume totals for individual currencies. Because of the pairs nature of trading, values represent double counting.

Currency	Trades	%	Volume ($)	%
AUD	514,210	6.43%	10,910,000,000	2.80%
BCO	1,340	0.02%	1,616,439	<0.01%
BGN	2	<0.01%	2,535	<0.01%
CAD	241,179	3.01%	4,996,100,000	1.28%
CHF	283,950	3.55%	9,111,300,000	2.34%
CLP	130	<0.01%	5,730,000	<0.01%
CNY	111	<0.01%	60,493	<0.01%
CZK	5,191	0.06%	514,025	<0.01%
DKK	992	0.01%	4,857,204	<0.01%
EUR	2,024,001	25.29%	131,400,000,000	33.76%
GBP	859,731	10.74%	37,800,000,000	9.71%
HKD	549	0.01%	7,278,893	<0.01%
HRK	2	<0.01%	20,000	<0.01%
HUF	458	0.01%	2,150,681	<0.01%
ILS	9	<0.01%	46,116	<0.01%
INR	240	<0.01%	389,671	<0.01%
JPY	696,725	8.71%	18,090,000,000	4.65%
KRW	9	<0.01%	36,000	<0.01%
LTL	1	<0.01%	10,000	<0.01%
MXN	1,799	0.02%	26,087,258	0.01%
NOK	5,233	0.07%	90,371,599	0.02%
NZD	194,499	2.43%	3,341,100,000	0.86%
PLN	730	0.01%	8,592,013	<0.01%
RON	5	<0.01%	6,246	<0.01%
RUB	90	<0.01%	515,250	<0.01%
SAR	39	<0.01%	5,360	<0.01%
SEK	4,015	0.05%	27,509,395	0.01%
SGD	3,648	0.05%	24,484,115	0.01%
SPX	128	<0.01%	2,142,500	<0.01%
THB	70	<0.01%	23,274	<0.01%
TRY	1,781	0.02%	38,299,257	0.01%
TWD	52	<0.01%	17,858	<0.01%
USD	3,066,467	38.32%	170,500,000,000	43.80%
WTI	183	<0.01%	3,188,826	<0.01%
XAG	25,752	0.32%	475,270,000	0.12%
XAU	67,352	0.84%	2,372,500,000	0.61%
XPT	4	<0.01%	38,508	<0.01%
ZAR	2,001	0.03%	20,810,326	0.01%

Table 3.4
Top 20 Traded Exchange Rates

Distribution of trade frequency and volume totals for exchange rate and currency pairs.

Currency	Trades	%	Volume ($)	%
EUR/USD	1,604,496	40.1%	118,300,000,000	60.8%
GBP/USD	538,585	13.5%	28,630,000,000	14.7%
AUD/USD	282,583	7.1%	6,859,500,000	3.5%
EUR/JPY	198,754	5.0%	5,749,800,000	3.0%
USD/JPY	188,823	4.7%	5,720,200,000	2.9%
GBP/JPY	138,866	3.5%	4,351,800,000	2.2%
USD/CHF	136,550	3.4%	3,701,100,000	1.9%
EUR/CHF	64,052	1.6%	3,660,700,000	1.9%
USD/CAD	138,704	3.5%	3,329,400,000	1.7%
XAU/USD	65,861	1.6%	2,341,300,000	1.2%
EUR/GBP	76,042	1.9%	2,305,900,000	1.2%
AUD/NZD	46,643	1.2%	1,357,600,000	0.7%
AUD/JPY	89,108	2.2%	1,262,400,000	0.6%
GBP/CHF	34,703	0.9%	1,157,800,000	0.6%
NZD/USD	68,565	1.7%	952,820,000	0.5%
EUR/CAD	26,625	0.7%	696,760,000	0.4%
GBP/NZD	30,318	0.8%	602,500,000	0.3%
EUR/AUD	33,106	0.8%	509,180,000	0.3%
XAG/USD	24,133	0.6%	465,940,000	0.2%
GBP/AUD	27,315	0.7%	462,230,000	0.2%
Others	187,507	4.5%	2,204,268,312	1.1%

Table 3.5
Distribution of Account Balances and Daily Returns

Distribution of daily performance and account balance information for social network members. Panel A account balance is in USD terms. Panel B returns exclude days with no market return.

Panel A: Account Balance

Observations:	4,302,702
25%	50
Median	574
75%	4,414
Mean:	78,293
Standard Deviation:	3,993,003
Skewness:	111.27

Panel B: Daily Returns

Observations:	4,302,702
25%	-0.0087824
Median	0.0000022
75%	0.0069774
Mean:	-0.0053146
Standard Deviation:	0.0798223
Skewness:	-1.4391290

Table 3.6
Distribution of Member "Friend" Connections

Distribution of the number of "friend" connections made by 5,901 members of a retail foreign exchange social network.

Observations:	5,901
25%	2
Median	6
75%	13
Mean:	14.14
Standard Deviation:	43.98
Skewness:	17.61

Table 3.7
Comparison of Social Network Member Quarterly Profitability Percentages to Broad Averages

Distribution of quarterly member account profitability rates compared to those reported by US brokers as mandated by the CFTC (Quarterly broker data aggregated by Forex Magnates - Greenberg, 2010, Greenberg, 2011c, Greenberg, 2011b, Greenberg, 2011a, Greenberg, 2011d, Greenberg, 2012d, Greenberg, 2012c, Greenberg, 2012a, Greenberg, 2012b, Finberg, 2013a, Finberg, 2013b, Greenberg, 2013, Siddiqui, 2013, Finberg, 2014). Profitability rates are based on accounts with at least one transaction in a given quarter.

Panel A: All Network Members

	Broker Reported			Social Network			
Quarter	Accts	Profitable	%	Accts	Profitable	%	Diff.
Q4 2009	92,024	25,943	28.2%	226	75	33.2%	5.0%
Q1 2010	81,289	21,854	26.9%	1,592	565	35.5%	8.6%
Q2 2010	106,650	28,176	26.4%	2,592	868	33.5%	7.1%
Q3 2010	100,320	29,026	28.9%	2,835	889	31.4%	2.4%
Q4 2010	108,361	31,242	28.8%	2,636	915	34.7%	5.9%
Q1 2011	108,513	34,620	31.9%	2,561	867	33.9%	1.9%
Q2 2011	106,945	28,765	26.9%	2,320	877	37.8%	10.9%
Q3 2011	108,490	32,512	30.0%	2,302	950	41.3%	11.3%
Q4 2011	97,206	33,953	34.9%	2,106	970	46.1%	11.1%
Q1 2012	97,281	32,370	33.3%	2,170	896	41.3%	8.0%
Q2 2012	93,687	29,884	31.9%	2,062	901	43.7%	11.8%
Q3 2012	101,020	32,731	32.4%	1,872	788	42.1%	9.7%
Q4 2012	89,567	32,131	35.9%	1,752	786	44.9%	9.0%
Q1 2013	99,207	34,918	35.2%	1,785	799	44.8%	9.6%
		Average:	30.8%		Average:	38.9%	8.0%

Panel B: Only US-based Network Members

	Broker Reported			Social Network			
Quarter	Accts	Profitable	%	Accts	Profitable	%	Diff.
Q4 2009	92,024	25,943	28.2%	75	25	33.3%	5.1%
Q1 2010	81,289	21,854	26.9%	592	198	33.4%	6.6%
Q2 2010	106,650	28,176	26.4%	932	297	31.9%	5.4%
Q3 2010	100,320	29,026	28.9%	1,014	309	30.5%	1.5%
Q4 2010	108,361	31,242	28.8%	870	278	32.0%	3.1%
Q1 2011	108,513	34,620	31.9%	814	232	28.5%	-3.4%
Q2 2011	106,945	28,765	26.9%	743	261	35.1%	8.2%
Q3 2011	108,490	32,512	30.0%	683	229	33.5%	3.6%
Q4 2011	97,206	33,953	34.9%	577	242	41.9%	7.0%
Q1 2012	97,281	32,370	33.3%	551	210	38.1%	4.8%
Q2 2012	93,687	29,884	31.9%	504	192	38.1%	6.2%
Q3 2012	101,020	32,731	32.4%	411	144	35.0%	2.6%
Q4 2012	89,567	32,131	35.9%	377	165	43.8%	7.9%
Q1 2013	99,207	34,918	35.2%	378	152	40.2%	5.0%
		Average:	30.8%		Average:	35.4%	4.6%

Figure 3.1 – Growth in Membership of a Trading Social Network

The social network began adding members in February 2009, though was initially only in a private (beta) period. It opened to the public later that year and began a phase of very rapid growth through aggressive marketing which lasted about 12 months.

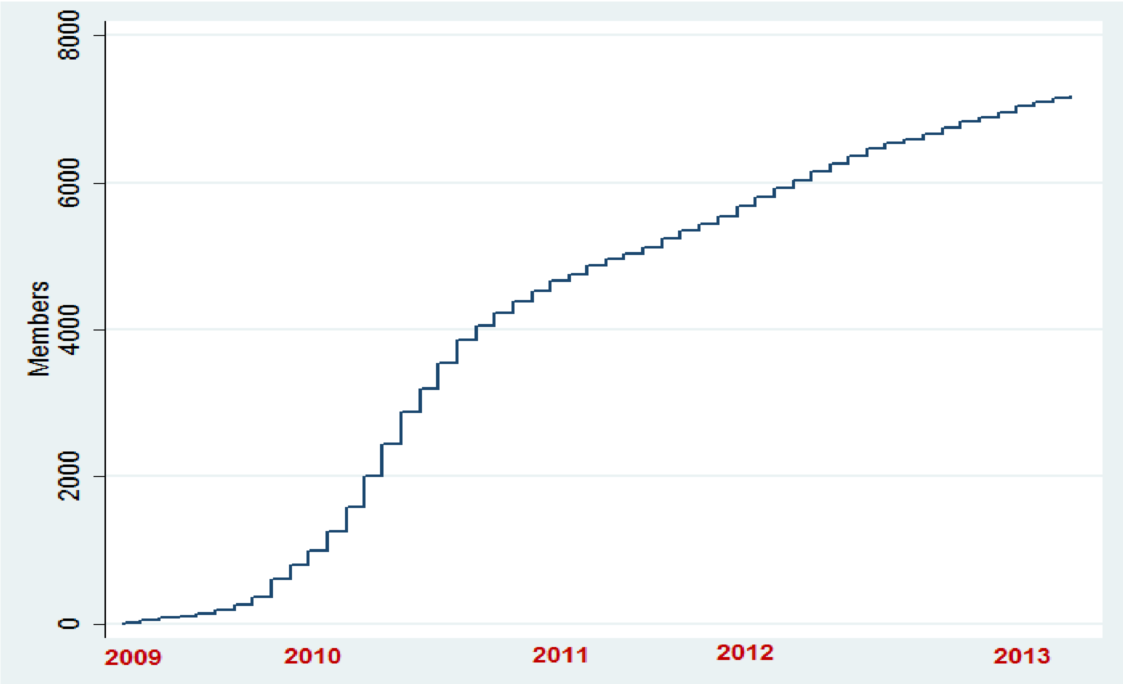


Figure 3.2 – Active Members of a Trading Social Network

The social network began adding members in February 2009, corresponding to Month 8 (prior months represent back-filled activity). The chart indicates the number of members who executed at least one trade during a given month.

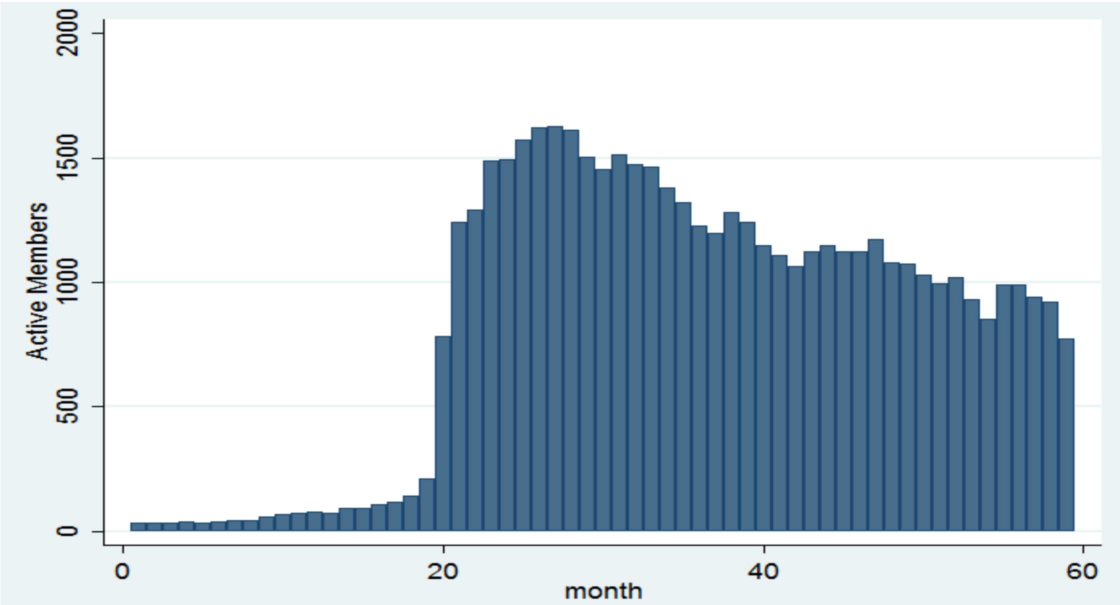


Figure 3.3 – Primary Language of Social Network Members

Distribution of the indicated preferred language of 7,180 confirmed retail foreign exchange traders in the social network. Despite the very strong bias toward English, the network is global with traders from all over the world. The English bias (86%) is to be expected for an English-language platform.

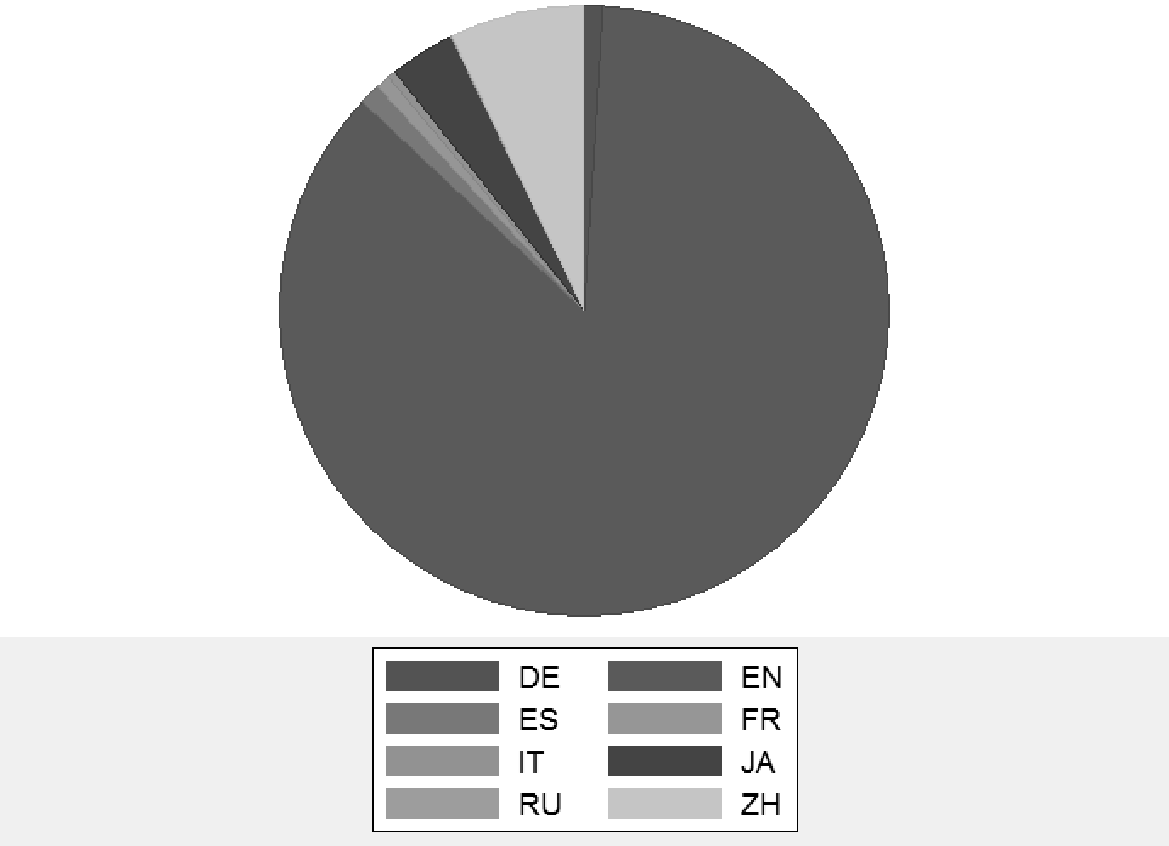


Figure 3.4 – Geographic Region of Social Network Members

Distribution of the indicated geographic region of 7,180 confirmed retail foreign exchange traders in the social network. Europe accounts for 35%, with the United States at 27%, and Asia/Pacific 17%. The “No Entry” category cannot be assumed to indicate an alternate region such as Africa or South America as it merely represents missing values.

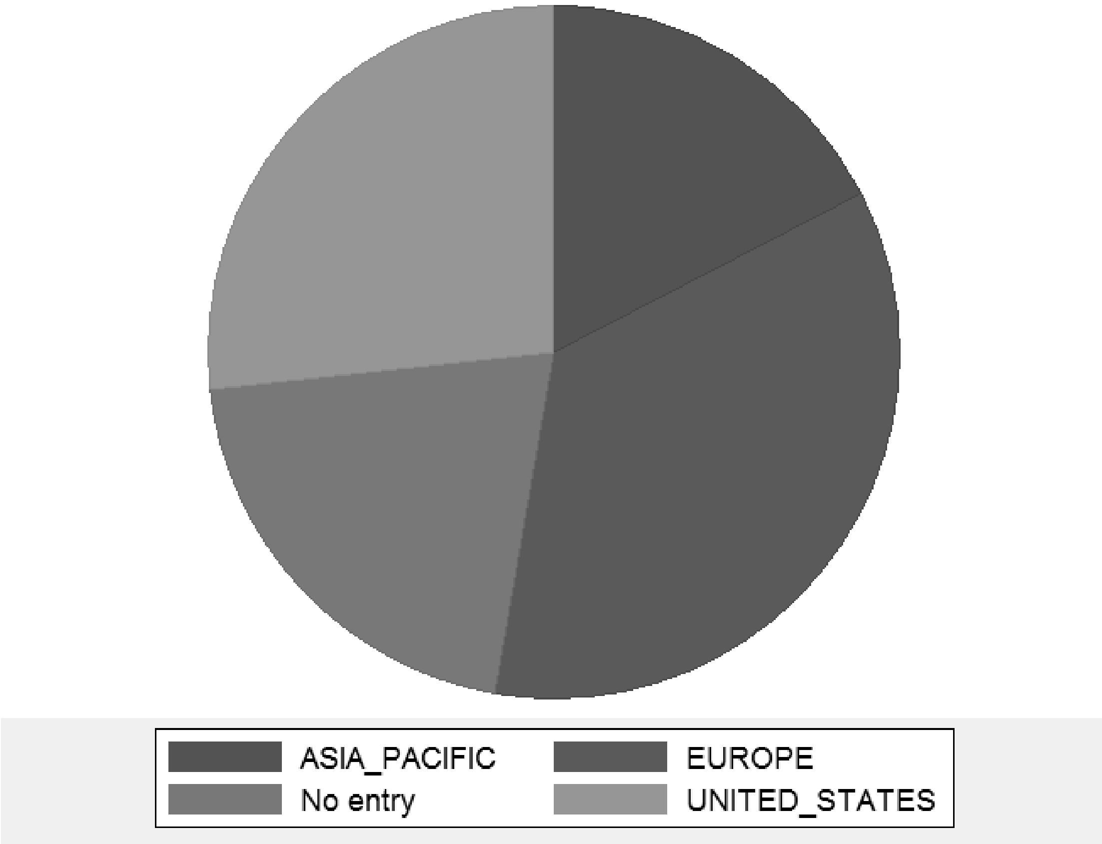


Figure 3.5 – Primary Trading Style of Social Network Members

Distribution of the indicated preferred trading style of 7,180 confirmed retail foreign exchange traders in the social network. Technical Analysis accounts for 54%, with momentum (4%), fundamental analysis (4%), news (2%) well behind. About 10% of members indicated no specific preference, with missing entries account for approximately 25%.

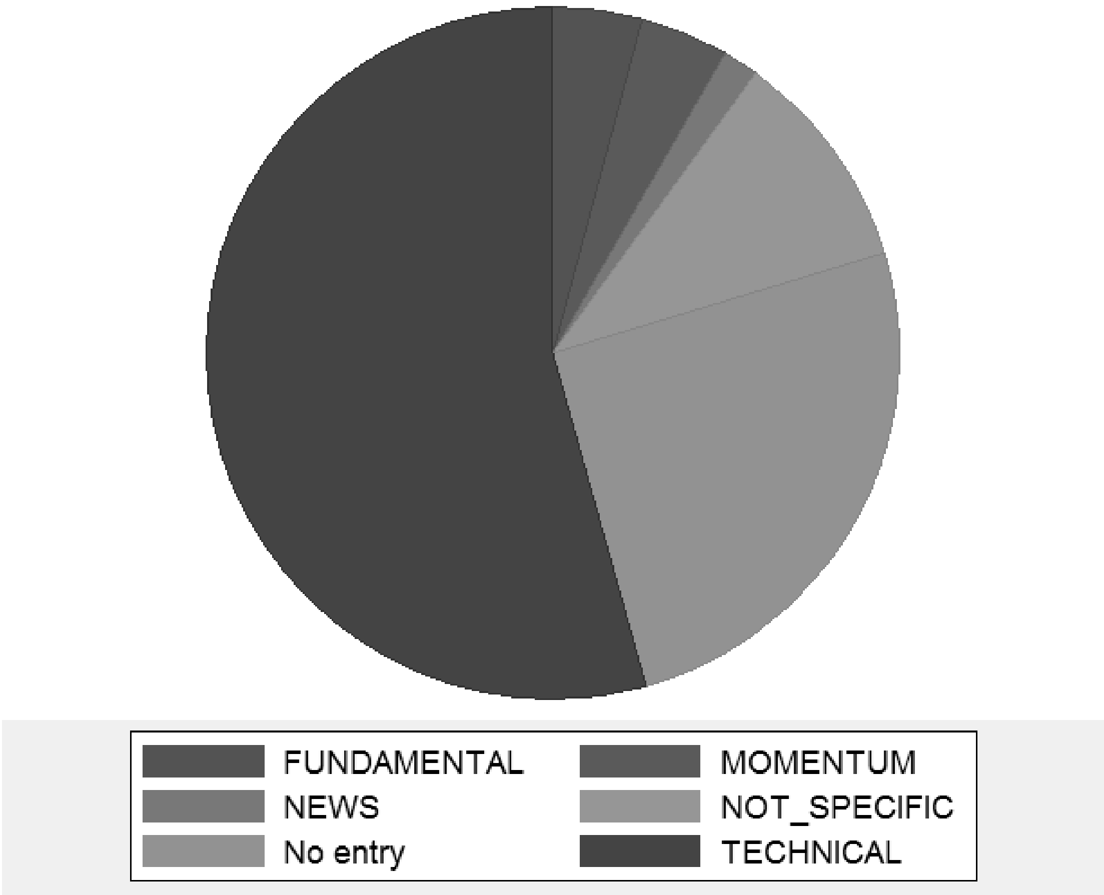


Figure 3.6 – Average Trades Per Week of Social Network Members

Distribution of the indicated average trades per week for 7,180 confirmed retail foreign exchange traders in the social network. The 10+ trades category is 39%, with 1-5 trades at 26%, while 6-10 trades is 18%. About 18% of members have no entry. Note, these are ranges indicated by the members in their profile, not the values actually seen in the transactional data.

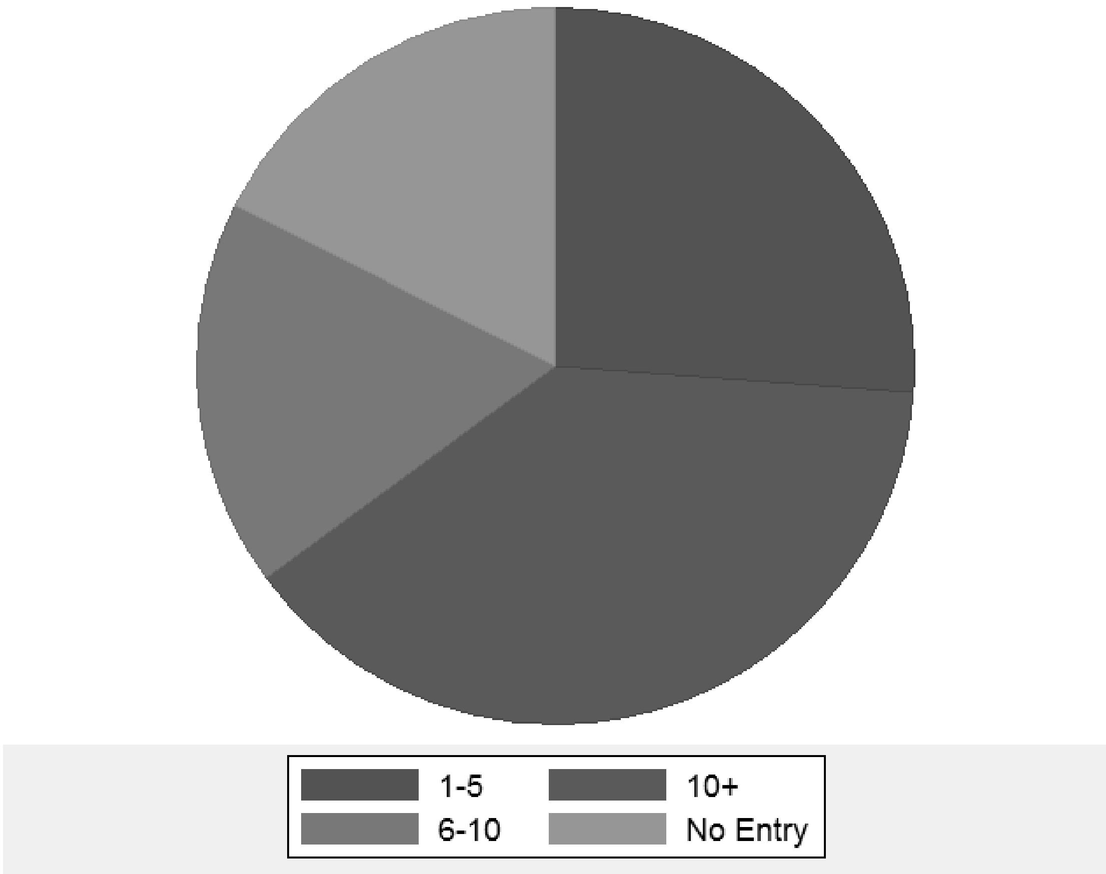


Figure 3.7 – Years of Trading Experience of Social Network Members

Distribution of the indicated years of trading experience for 7,180 confirmed retail foreign exchange traders in the social network. Note that these values are taken from entries in the trader member profile. Assuming they have mainly not been updated since an individual joined the network, they indicate experience at the time of becoming a member.

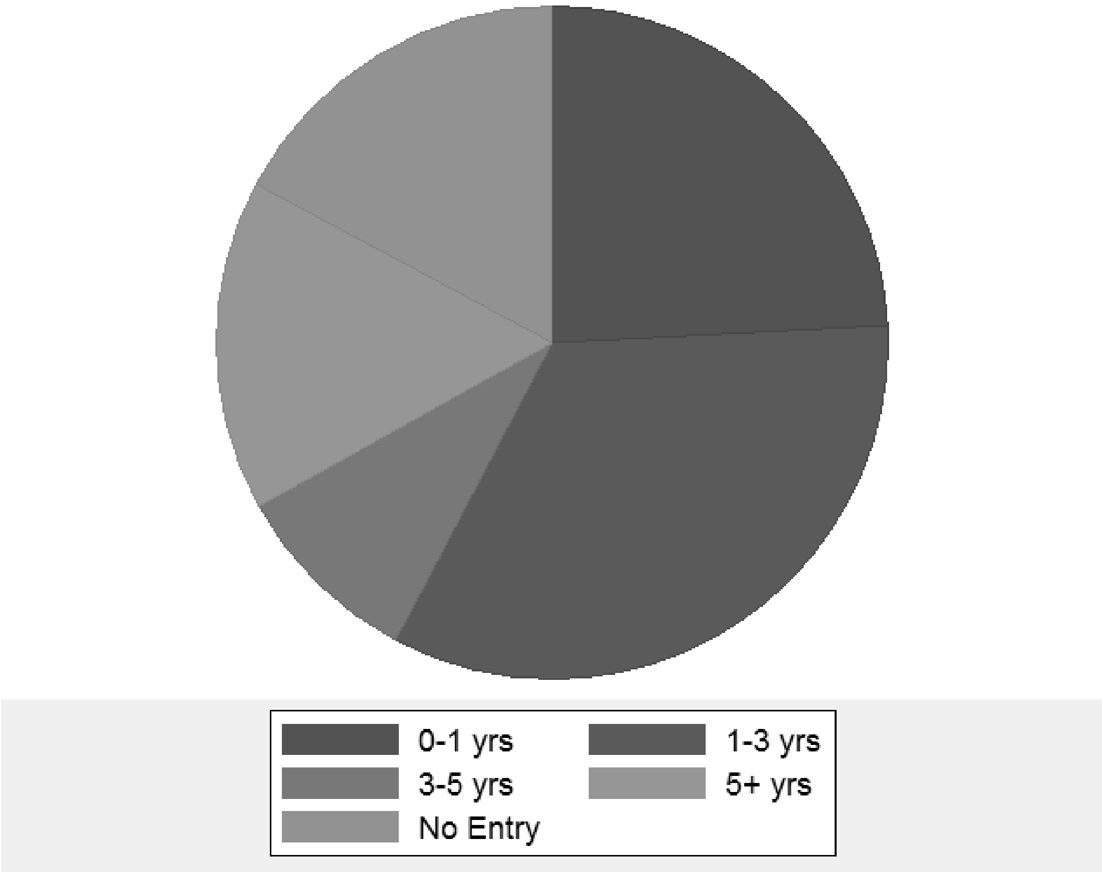


Figure 3.8 – Performance Privacy Choices of Social Network Members

Distribution of the privacy option of 7,180 confirmed retail foreign exchange traders in the social network. This setting defines who is able to view a member's trading activity and performance. The possible settings are Public for any visitor to the website, Community for only logged-in members of the network, Virtual Trading Team (VTT) for those with whom a member has linked as "friends", or Owner for only themselves.

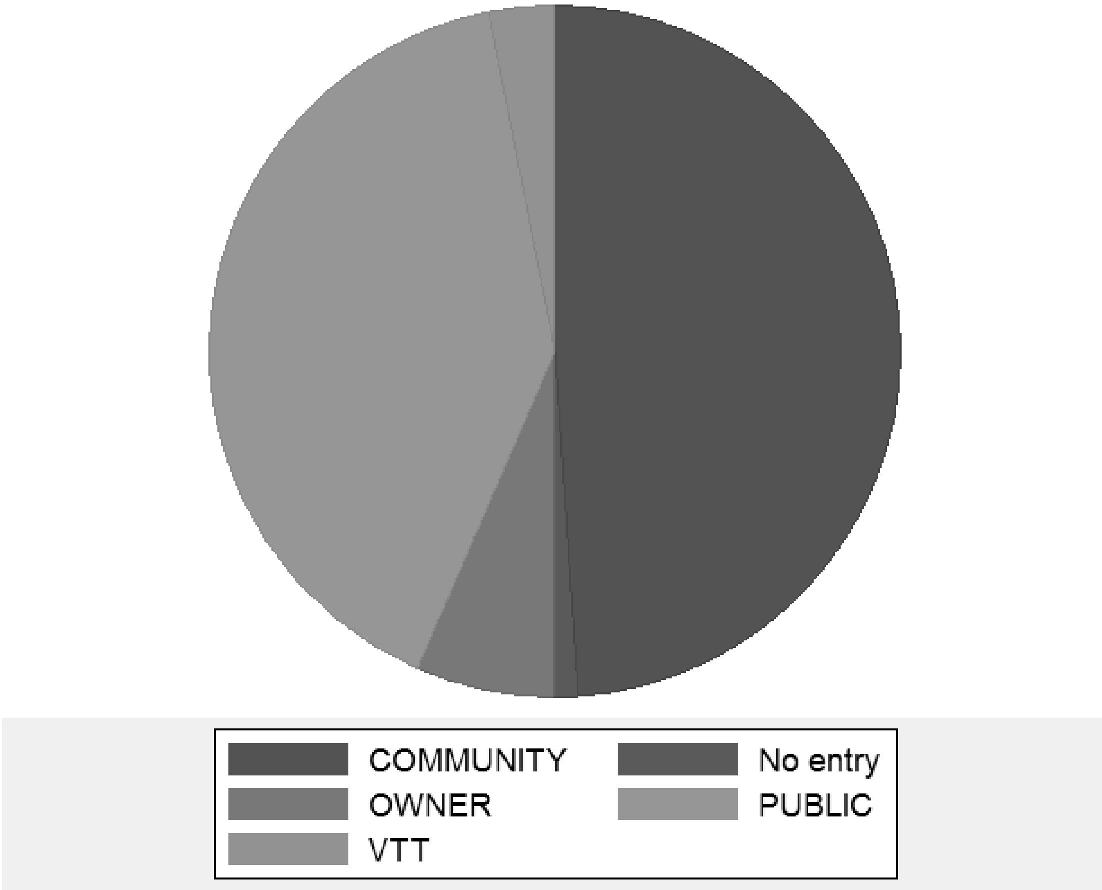


Figure 3.9 – Ages at Registration for Members of a Trading Social Network

Distribution of the ages of 7,180 retail foreign exchange traders (exclusive of missing values) in the social network as of their date of registration. Youngest is 16.2 years, oldest 94.5 years. Mean age is 36.8 years. Median is 34.6 years. The 25% to 75% range is 28.3 - 43.2 years.

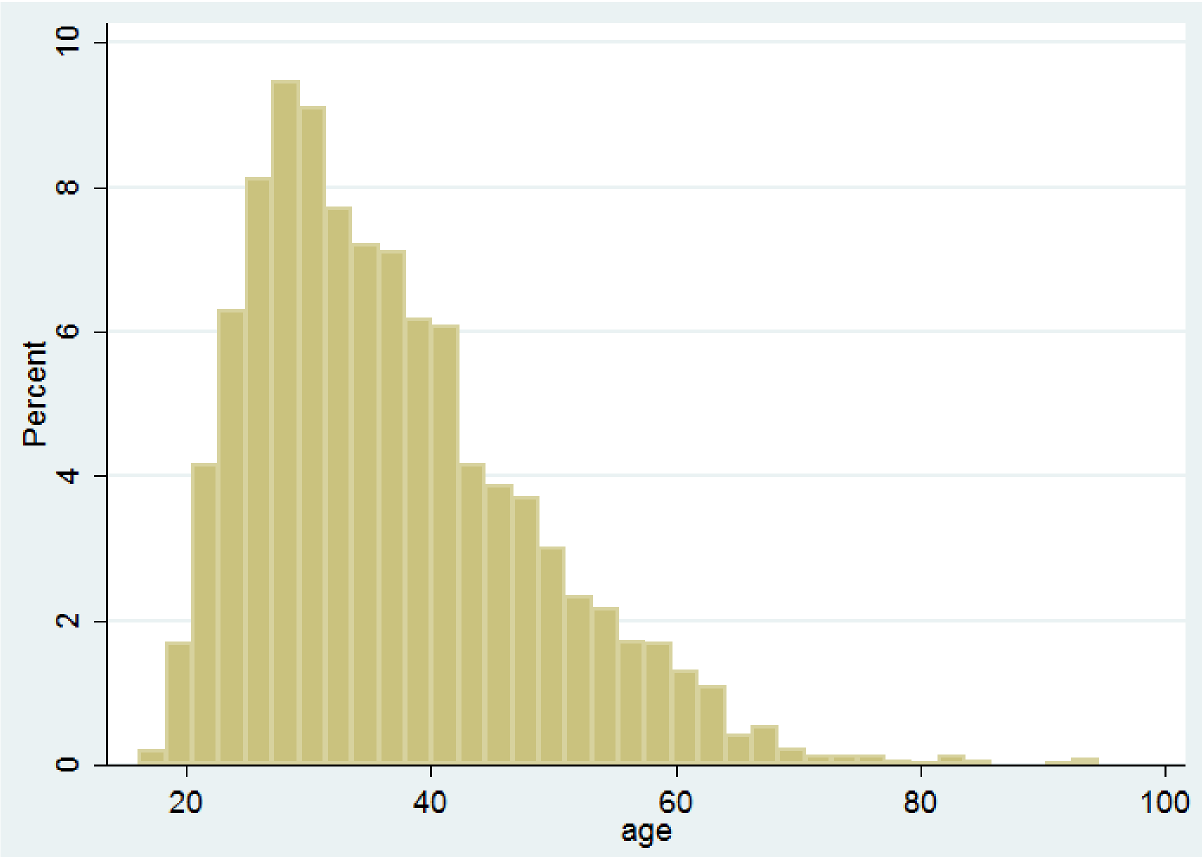
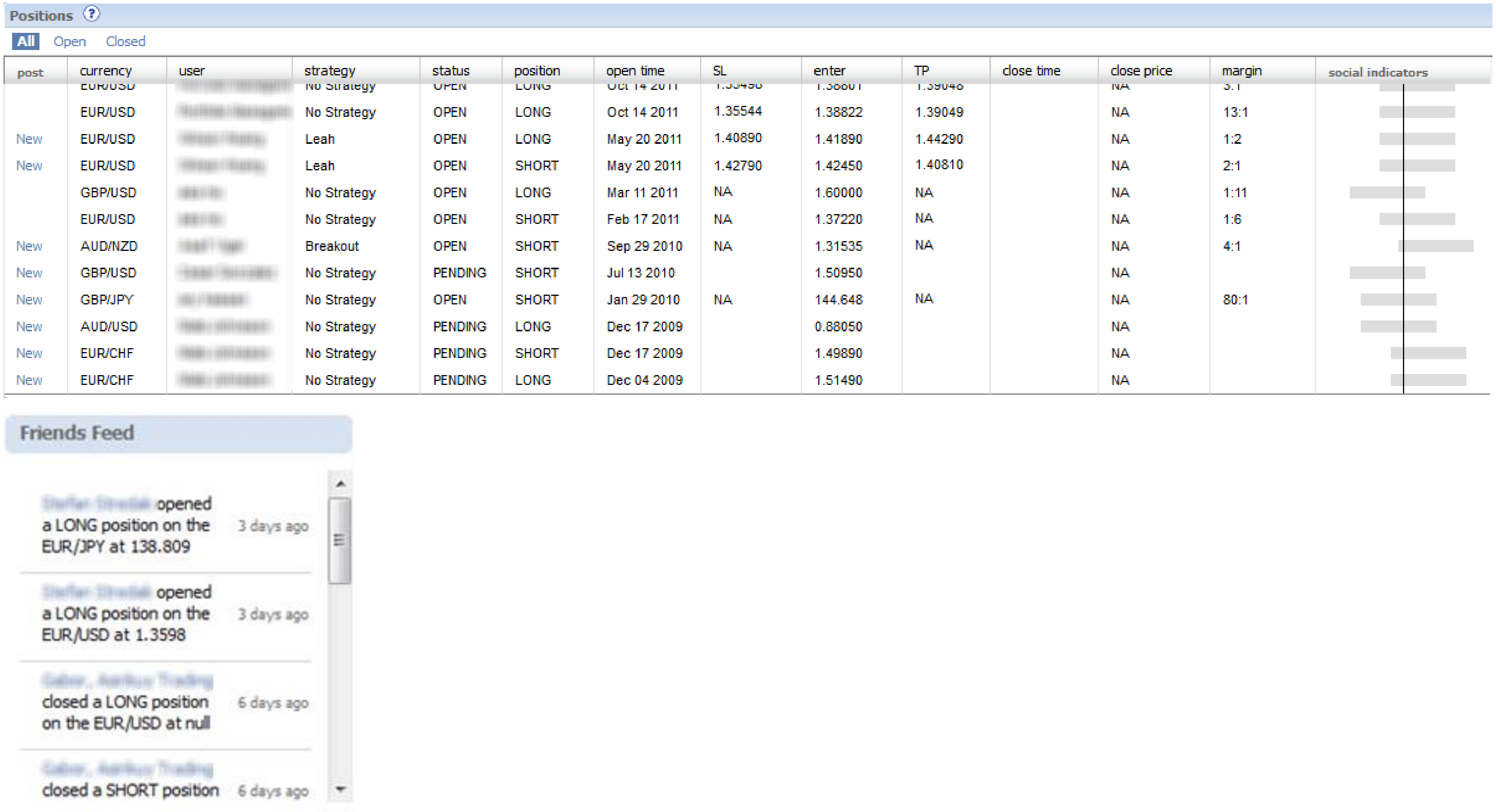


Figure 3.10 – Social Network Information

Sample indication of "friend" trading positions and activity displayed to members of the social network.



Positions

All Open Closed

post	currency	user	strategy	status	position	open time	SL	enter	TP	close time	close price	margin	social indicators
	EUR/USD		No Strategy	OPEN	LONG	Oct 14 2011	1.35498	1.38801	1.39048		NA	3:1	
	EUR/USD		No Strategy	OPEN	LONG	Oct 14 2011	1.35544	1.38822	1.39049		NA	13:1	
New	EUR/USD		Leah	OPEN	LONG	May 20 2011	1.40890	1.41890	1.44290		NA	1:2	
New	EUR/USD		Leah	OPEN	SHORT	May 20 2011	1.42790	1.42450	1.40810		NA	2:1	
	GBP/USD		No Strategy	OPEN	LONG	Mar 11 2011	NA	1.60000	NA		NA	1:11	
	EUR/USD		No Strategy	OPEN	SHORT	Feb 17 2011	NA	1.37220	NA		NA	1:6	
New	AUD/NZD		Breakout	OPEN	SHORT	Sep 29 2010	NA	1.31535	NA		NA	4:1	
New	GBP/USD		No Strategy	PENDING	SHORT	Jul 13 2010		1.50950			NA		
New	GBP/JPY		No Strategy	OPEN	SHORT	Jan 29 2010	NA	144.648	NA		NA	80:1	
New	AUD/USD		No Strategy	PENDING	LONG	Dec 17 2009		0.88050			NA		
New	EUR/CHF		No Strategy	PENDING	SHORT	Dec 17 2009		1.49890			NA		
New	EUR/CHF		No Strategy	PENDING	LONG	Dec 04 2009		1.51490			NA		

Friends Feed

opened a LONG position on the EUR/JPY at 138.809 — 3 days ago

opened a LONG position on the EUR/USD at 1.3598 — 3 days ago

closed a LONG position on the EUR/USD at null — 6 days ago

closed a SHORT position — 6 days ago

Figure 3.11 – Position Balances amongst Members

Balance of social network trader positions in various currency pairs. Snapshot taken April 4, 2014 during US morning trading hours from Thomson Reuters.

currency	price
EUR/USD	1.36023
GBP/USD	1.71264
USD/JPY	101.845
EUR/GBP	0.79416
USD/CAD	1.06648
AUD/USD	0.93686
AUD/CAD	0.99924
AUD/JPY	95.420
AUD/NZD	1.06941
CAD/CHF	0.83766
CAD/JPY	95.483
CHF/NOK	6.89944
CHF/SEK	7.64686
EUR/AUD	1.45173
EUR/CAD	1.45073
EUR/CHF	1.21542
EUR/JPY	138.539
EUR/NOK	8.38687
EUR/NZD	1.55261
EUR/SEK	9.29524
EUR/TRY	2.89697
GBP/AUD	1.82779
GBP/CAD	1.82665
GBP/CHF	1.53028
GBP/JPY	174.432
GBP/NOK	10.55899
GBP/SEK	11.70287
NOK/JPY	16.513
NZD/CAD	0.93418
NZD/JPY	89.206
NZD/USD	0.87596
SEK/JPY	14.899
SGD/JPY	81.678
USD/CHF	0.89347
USD/NOK	6.16545
USD/SEK	6.83319
USD/SGD	1.24650
USD/TRY	2.12922

social indicators

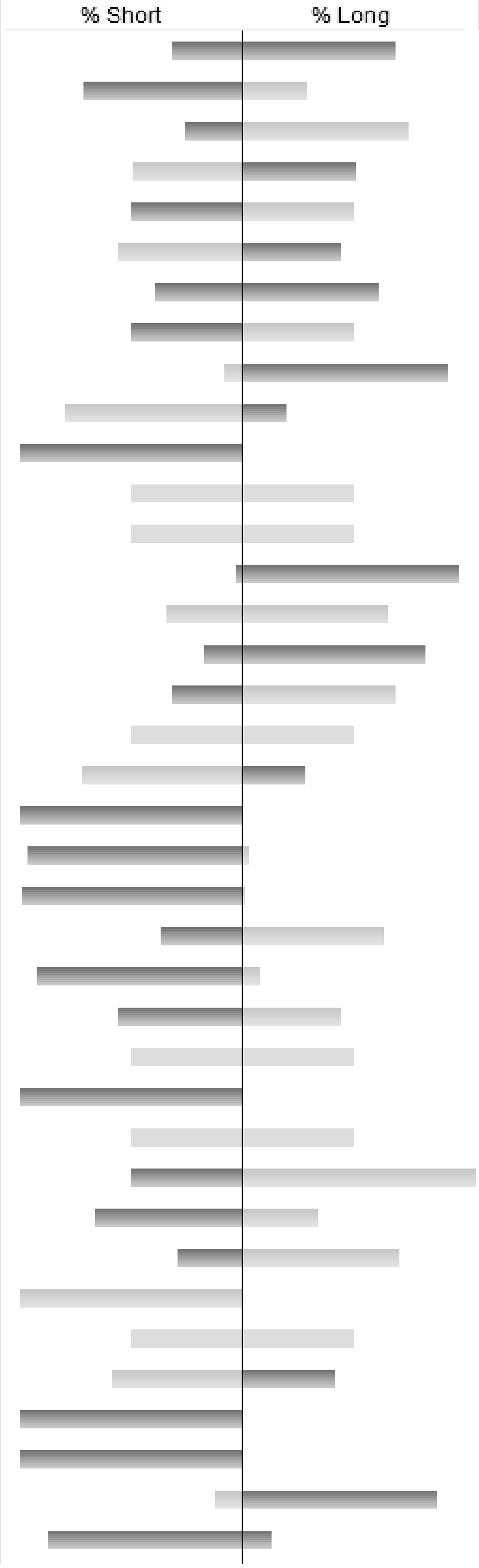


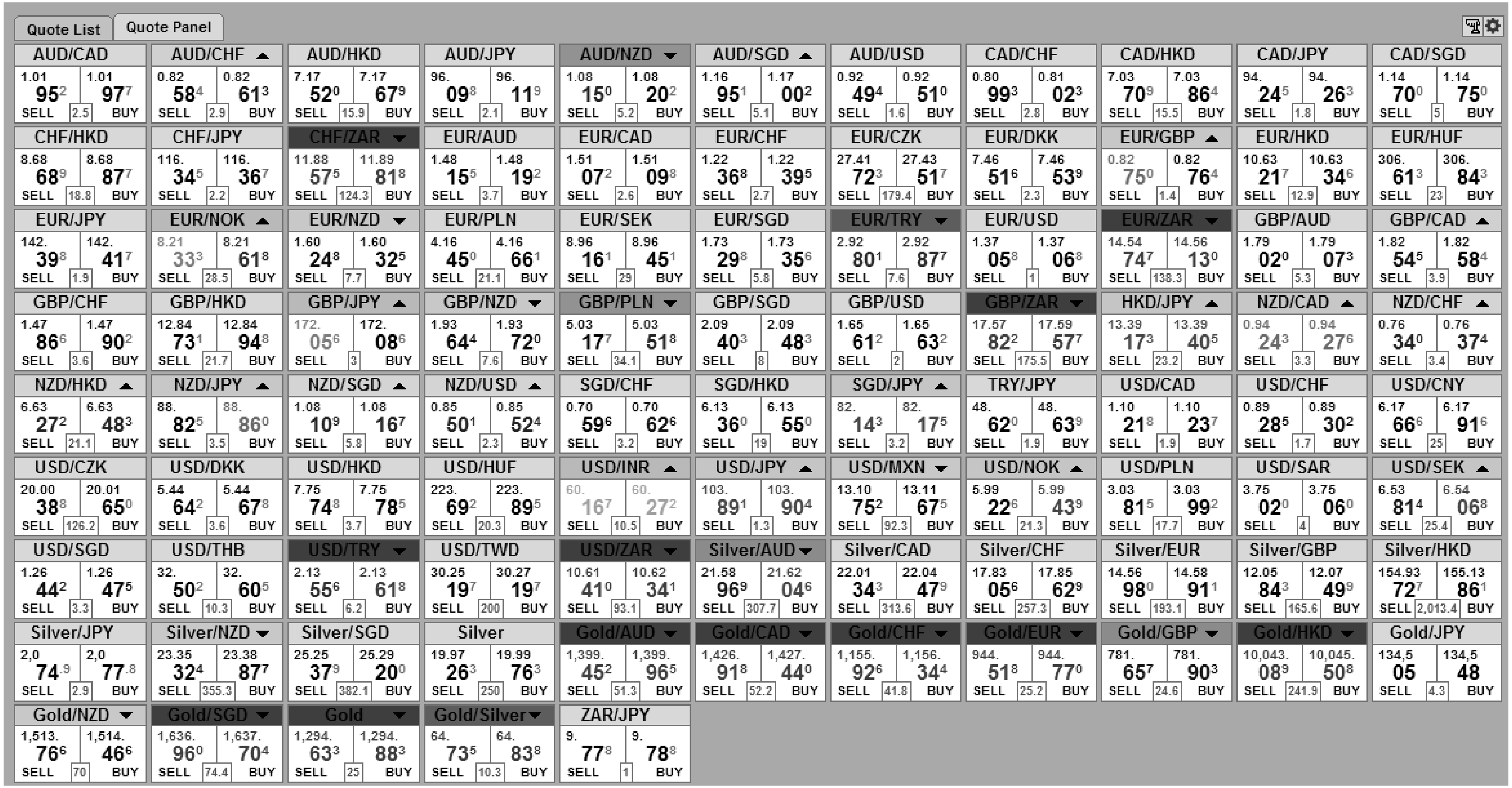
Figure 3.12 – Sample Exchange Rate Spreads

Snapshot of bid and ask exchange rates taken April 4, 2014 during US morning trading hours from Thomson Reuters.

AUDDKK=R	Reuters	5.0197	+5.0551	5.0551	5.0566	14:16	4/4/2014	DKK	Reuters
AUDNOK=	S E A ASIA SIN	5.5256	+5.5338	5.5338	5.5339	10:01	4/4/2014		S E A ASIA
AUDPLN=	ZACHODNI WBK WAW	2.8020	+2.8185	2.8185	2.8210	14:16	4/4/2014	PLN	ZACHODNI WBK
AUDZAR=R	Reuters	9.7744	+9.7729	9.7729	9.7797	14:16	4/4/2014	ZAR	Reuters
CADCZK=R	Reuters	18.1065	+18.2178	18.2178	18.2340	14:16	4/4/2014	CZK	Reuters
CADDKK=R	Reuters	4.9276	+4.9591	4.9591	4.9600	14:16	4/4/2014	DKK	Reuters
CADMXN=R	Reuters	11.8796	+11.8656	11.8656	11.8758	14:16	4/4/2014	MXN	Reuters
CADNOK=	NORDEA COP	5.4411	+5.4567	5.4567	5.4584	14:16	4/4/2014		NORDEA
CHFNOK=R	Reuters	6.7337	+6.7080	6.7080	6.7118	14:16	4/4/2014	NOK	Reuters
CHFPLN=R	Reuters	3.4046	+3.4044	3.4044	3.4066	14:16	4/4/2014	PLN	Reuters
CHFSEK=	SEB STO	7.3361	+7.3163	7.3163	7.3316	14:14	4/4/2014		SEB
CHFSGD=R	Reuters	1.4171	+1.4130	1.4130	1.4139	14:16	4/4/2014	SGD	Reuters
EURILS=	1ST INTL BK TLV	4.7588	+4.7666	4.7666	4.7696	14:16	4/4/2014	ILS	1ST INTL BK
EURINR=	RBS LON	82.6800	+82.0000	82.0000	82.0700	14:16	4/4/2014		RBS
EURMXN=	BC SANTANDER NYC	17.9889	+17.8579	17.8579	17.8674	14:16	4/4/2014	MXN	BC SANTANDER
EURRON=	ING BANK BUM	4.4669	+4.4568	4.4568	4.4633	14:16	4/4/2014	RON	ING BANK
EURRUB=	CITIBANK MOW	48.8090	+48.3290	48.3290	48.3470	14:16	4/4/2014	RUB	CITIBANK
GBPBGN=	UNICR BULBK SOF	2.3665	+2.3660	2.3660	2.3668	14:16	4/4/2014	BGN	UNICR BULBK
GBPDKK=	RBS XST	9.0280	+9.0337	9.0337	9.0356	14:16	4/4/2014	DKK	RBS
GBPMXN=R	Reuters	21.7631	+21.6069	21.6069	21.6261	14:16	4/4/2014	MXN	Reuters
GBPNOK=	ALLIED IRISH DUB	9.9580	+9.9260	9.9260	9.9320	14:16	4/4/2014	NOK	ALLIED IRISH
GBPSEK=	RBS XST	10.8440	+10.8427	10.8427	10.8471	14:16	4/4/2014	SEK	RBS
MXNJPY=R	Reuters	7.9195	+7.9601	7.9601	7.9670	14:16	4/4/2014	JPY	Reuters
NOKJPY=R	Reuters	17.3085	+17.3374	17.3374	17.3431	14:16	4/4/2014	JPY	Reuters
NOKSEK=	RBS LON	1.0883	+1.0905	1.0905	1.0919	14:16	4/4/2014	SEK	RBS
NZDDKK=R	Reuters	4.6461	+4.6768	4.6768	4.6789	14:16	4/4/2014	DKK	Reuters
NZDNOK=R	Reuters	5.1255	+5.1405	5.1405	5.1435	14:16	4/4/2014	NOK	Reuters
SEKJPY=R	Reuters	15.8942	+15.8689	15.8689	15.8778	14:16	4/4/2014	JPY	Reuters
BGN=	UNICR BULBK SOF	1.4254	+1.4264	1.4264	1.4267	14:16	4/4/2014	BGN	UNICR BULBK
CLP=	SANTANDER MAD	556.10	+554.40	554.40	554.70	14:16	4/4/2014	CLP	SANTANDER
HRK=	HSBC LON	5.5567	+5.5697	5.5697	5.5713	14:16	4/4/2014	HRK	HSBC
ILS=	1ST INTL BK TLV	3.4703	+3.4725	3.4725	3.4825	14:16	4/4/2014	ILS	1ST INTL BK
KRW=	SOC GEN NYC	1057.50	+1053.85	1053.85	1054.75	13:33	4/4/2014	KRW	SOC GEN
LTL=	DANSKE BANK COP	2.5156	+2.5174	2.5174	2.5192	14:16	4/4/2014	LTL	DANSKE BANK
RUB=	SBERBANK CIB MOW	35.5675	+35.2300	35.2300	35.2600	14:16	4/4/2014	RUB	SBERBANK CIB
/CLc1	LIGHT CRUDE MA/d	100.29	+101.27	101.27	101.28	14:05	4/4/2014	USD	NYM
/SPY	SPDR S&P 500/d	188.63	+189.57	189.57	189.5900	21:00	4/4/2014	USD	
XPT=	ICAP LON	1435.80	+1441.49	1441.49	1449.00	14:16	4/4/2014	USD	ICAP LON
/LCOc1	BRENT CRUDE MA/d	106.15	+106.78	106.78	106.79	14:05	4/4/2014	USD	

Figure 3.13 – Sample Exchange Rate Spreads

Snapshot of bid and ask exchange rates taken April 4, 2014 during US morning trading hours from OANDA FXTrade platform.



Chapter 4: Leverage and Overconfidence

4.1. Introduction

In the financial markets, individuals are often told not to over-trade as a key factor in avoiding major performance issues. This advice addresses two considerations. One is trading too often. The other is trading too large relative to one's capital. In other words, do not use too much leverage – leverage in this case simply being a multiple applied to account balance (e.g. leverage of 3:1 would mean trading a $3,000 position on a $1,000 account).

While perhaps not couched in such terms, the major admonishment in this sort of advice is to avoid overconfident trading. Given the research indicating negative effects from being active in the markets as an individual, such as Barber and Odean (2000), it could be suggested that simply trading on an individual basis at all is an indication of overconfidence, especially when taking part in a zero/negative-sum game type market structure or environment. Of course, things are not so simple. The fact is that some investors are successful in the markets. It may only be a small fraction, as Barber et al. (2013) document, but it exists and one cannot determine whether they have the requisite skill to be among that group without actually trading. This introduces questions as to the value of looking at certain trading activity metrics commonly used the literature (monthly account turnover primarily, trade frequency secondarily) in attempting to identify overconfidence, and whether others such as leverage would be better.

The subject of leverage in trading and investing has thus far received little in the way of research attention, with only the very recent Heimer (2013) work taking a specific interest with a link to overconfidence, and Linnainmaa (2003) relating leverage and returns, but without a strong view toward causality.[39] The primary focus of the published work to-date is on more macro level price and market impacts of leverage use and constraints thereof (Mayhew et al., 1995, Kupiec and Sharpe, 1991, Hardouvelis and Theodossiou, 2002, Foucault et al., 2011, Hsieh and Merton, 1990, Hardouvelis and Kim, 1995, Moore, 1966, Wang, 2013). Leverage, however, is commonly used by high

[39] What causality is suggested is in the direction of the disposition effect rather than overconfidence.

frequency market participants such as day traders. For this reason, the study of its implementation by practitioners is important in understanding market activity and price movement in short-term time frames since it relates directly to the volumes transacted.

This chapter serves two main purposes. First, it extends prior overconfidence research into the forex market, which offers the opportunity for examining behaviour in a more high-frequency arena. Second, it focuses on the use of leverage as an indication of overconfident trading behaviour. From the latter perspective, to the extent that the recognition of increased leverage points to increasingly questionable decision-making by traders, which is suggested by Burks et al. (2013), the opportunity exists for corrective action to be employed to improve performance. Further, to the extent that increased leverage use is observed in aggregate, it can potentially be employed as an indication of irrational market behaviour and as such it would facilitate improved risk management strategies.

The remainder of this chapter is structured as follows. Section 4.2 reviews the prior literature and develops the primary hypotheses of the chapter. Section 4.3 provides documentation of the data and methodologies being employed in the research, with Section 4.4 containing the analysis. Section 4.5 concludes and presents considerations for future research.

4.2. Literature Review and Hypotheses

4.2.1. Foundations

In the Barberis and Thaler (2003) review, the classical paradigm of financial theory is described as seeking to understand the financial markets by employing assumptions of participant rationality. For rationality to hold, actors must properly update their beliefs upon receipt of new information, as defined by Bayes' law, and with those updated beliefs make choices which are normatively acceptable on the basis of Subjective Expected Utility (SEU). While elegant, however, models based on this rationality have consistently come up short in attempting to define and predict real life. Consequently, the field of behavioural finance research has developed as an alternative approach to try to understand the actions of individuals, and by extension markets. It does so through the relaxation of rationality assumptions. In other words, behavioural theorists derive models based on the idea that agents fail to properly update their beliefs and/or act on the basis of decisions which are not necessarily SEU compatible.

While accepting that such less-than-fully-rational agents exist, the classical finance arguments against these behavioural models centre on the influence of said agents in markets where there also exists fully rational actors. These fully rational actors are able to counter any influence on prices created by their less-than-fully rational counterparts. The area of research known as “limits to arbitrage” provides a counterpoint by suggesting that rational actors are constrained in their ability to offset the influence of irrationality. These constraints include issues such as limited capital, imperfect substitution, implementation costs, and noise trader risk (de Long et al., 1990, Shleifer and Vishny, 1997). This then allows behavioural researchers to make the case that less-than-fully-rational agents can and do have a persistent influence on prices (Shleifer and Summers, 1990, Kyle and Wang, 1997, Kogan et al., 2006).

Alongside the research into the limits to arbitrage, a second primary path of behavioural study is in the area of psychology, specifically related to systemic cognitive biases in beliefs and preferences. In other words, while the limits to arbitrage research focuses on how markets and agents act in the face of less-than-fully-rational actors, this second area of study focuses on the sources and drivers of irrationality.

One of the major themes on this psychological side of the behavioural research is violations of expected utility. At the forefront of this study is prospect theory, which is defined in Kahneman and Tversky (1979). Prospect theory, based on the findings of experimental research, focuses on decision-making under uncertainty and shows how individuals violate expected utility by weighting gains and losses differently (while not focusing on final wealth, as would be expected). Extension of these observations led to the development of the disposition effect in Shefrin and Statman (1985) which theorizes that financial market participants are biased toward quickly realizing gains to avoid seeing them slip away while being slow to take losses in hopes the market will turn around, an example of the failure of rationality in choices on the basis of SEU.[40]

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[40] The disposition effect is tested empirically in Odean (1998a).

The other major theme of the behavioural research from the psychological perspective is in the area of overconfidence. The psychology literature provides ample evidence that individuals are overconfident and that overconfidence comes in two primary forms. One is that people fail in their estimates of probabilities, particularly in the case of perceived certain or impossible events. The other is that they are too narrow in defining confidence intervals. Thus, individuals fail to properly update their beliefs per Bayes' rule. From the perspective of financial market agents, as observed by Kahneman and Riepe (1998), the implication of overconfidence is that individuals overestimate their ability to make investments or trades with positive expected returns, or which outperform the market on a net basis. As Burks et al. (2013) assert, to the extent that overconfidence is a judgement bias it raises "*…the possibility that individuals systematically make suboptimal decisions because they choose based on biased beliefs.*"

Daniel et al. (1998) also bring the overconfidence discussion into the financial markets realm by showing how prices overreact to private information which overconfident investors overweight, while prices underreact to public information which gets underweighted. This produces a negative autocorrelation in stock returns, along with unconditional excess volatility. Daniel et al. (2001) then extend this argument by theorizing a link between the cross section of expected security returns and a combination of risk and the misuse of information by investors in decision-making.

4.2.2. Overconfidence implications on trading activity

In Odean (1998b) it is theorized that overconfidence among investors leads to increased trading volume and by extension decreased utility as individuals fail to overcome the costs associated with the additional transactions. This is supported empirically by Barber and Odean (2000) in an evaluation of investor portfolio turnover. Statman et al. (2006) similarly find that overconfidence on the basis of the misattribution of market returns to individual skill drives increased stock market turnover. Barber et al. (2009a) draw a similar conclusion from analysis of trading in the Taiwan stock market that overconfidence factors into trading volume, with sensation-seeking also indicated as a potential motivator, resulting in a significant annual loss to financial speculation.[41] Narrowing the focus, Gervais and Odean (2001) provide a model whereby early-career investors are overconfident, resulting in more aggressive trading, which leads to higher expected trading volume. Statman et al. (2006) take a market-centric view rather than an investor-centric one and similarly find evidence for overconfidence (and disposition effect) trading on the basis of prior returns in the turnover pattern of individual stocks.

Support for the Odean (1998b) assertion is also presented in the analysis of gender with respect to overconfidence in Barber and Odean (2001a), and then extended by Grinblatt and Keloharju (2009) wherein analysis of psychological assessments and speeding ticket records for participants in the Finnish stock market is made. Positive correlations between both those measures and trading activity (viewed in terms of both turnover and trade frequency) strengthen the case for overconfidence and sensation-seeking tendencies impacting investor behaviour. Grinblatt and Keloharju (2009) also examine returns as they may relate to overconfidence, but beyond observing that all relative returns are worse across all defined levels of overconfidence and sensation-seeking they hesitate to draw any real conclusions.

The idea that increased trading activity drives reduced performance, and thus should be viewed as indicative of overconfidence or some other behavioural issue, is partially challenged by Garvey and Murphy (2005), however. The metric for trading activity in this instance is trade frequency rather than volume or turnover. No link is found between the number of trades executed and trader performance. Unfortunately, the dataset used includes a meaningful number of professional traders rather than being strongly biased toward non-professionals. If it is assumed that professionals are more likely to be rational actors who will only trade when they have a statistical advantage, then it would follow that they would not experience lessened performance when trading more actively. Quite the opposite, in fact.

Still, the Garvey and Murphy (2005) findings bring the question of the value of looking at trading frequency up for review. Grinblatt and Keloharju (2009) do use it as a metric, suggesting that sensation-seeking investors are likely to trade more frequently. There are other potential drivers of trade frequency as well, however, which may tend to challenge it as a useful measure

[41] French (2008) makes a similar case regarding the cost to society of active investing strategies.

of either overconfidence or sensation-seeking. In particular, research looking at investors from a learning perspective makes the case that individuals still trying to assess their trading talent may trade more than rational expectations would suggest.

An example of this theorization is a learning model of speculation proposed in Mahani and Bernhardt (2007) which features small-scale trading by inexperienced traders as they seek to discover their skill level. The suggestion here is that while inexperienced traders may trade more actively in frequency terms during the learning process, they may not actually trade at very high relative turnover levels. Linnainmaa (2011) supports this idea, at least in part, by reporting that some traders use very small positions to learn about their ability. Thus, there theoretically exists a group of market participants who may be trading more frequently than rational expectations would suggest, but doing so on a relatively small scale. This is very similar to the trading pattern proposed by Grinblatt and Keloharju (2009) in terms of sensation-seeking individuals. Therefore, it may be a struggle to differentiate learning from behavioural bias on the basis of trade frequency.

Additionally problematic in looking at the activity of traders is the implication for performance of the idea that lower levels of activity are linked to better relative returns. Research supports the case for the role of trading maturity in returns, with Nicolosi et al. (2009) and Seru et al. (2010) both finding a positive link between investor experience and performance, presumably at least part of which includes developing the ability to overcome behavioural biases [which features in the Gervais and Odean (2001) model]. There is additionally the question of investor sophistication. It factors positively into the equation, as outlined by Feng and Seasholes (2005), and further links higher levels of experience with lower behavioural bias influence (the disposition effect in particular). Thus, if the Odean (1998b) expectation of returns being negatively correlated to trading activity holds, one would expect to see more experienced and sophisticated traders operating at the lowest activity levels. Even if rationally increased trading activity on the basis of positive expectancy is left to the side, however, there is the finding of Graham et al. (2009) linking experience with increased activity.

4.2.3. Increased focus on speculative activity

The focus of much of the early empirical research into market participant behaviour on relatively inactive individuals (investors rather than traders) has two major short-comings. One is that inactive investors offer relatively few decisions against which to measure the potential impact of overconfidence and other biases, or their learning to overcome them. The second is that inactive investors are not significant contributors to the short-term movement of prices, thus limiting the potential to analyse higher frequency price movements.

The lack of research into the more high frequency trader population is starting to be addressed in the literature as new data sources become available. Jordan and Diltz (2003) provide one of the early empirical studies of active speculator behaviour. Looking at approximately nine months of order data from a US brokerage focused on day trading, they conclude that only about one trader in three is profitable and just 20% are more than marginally so, with trader performance broadly linked to market performance. As noted above, Garvey and Murphy (2005) evaluate stock market day traders, suggesting that under-skilled traders underwrite their more skilled counterparts. Thus, there are indications of the influence of skill in returns.

Extending on the skill theme, Barber et al. (2013) provide what they describe as the first large-scale analysis of speculative activity in their research based on 15 years of activity for day traders in Taiwan. Here the focus is on cross-sectional analysis of speculator skill. The authors find that only a small fraction of traders are persistently profitable after accounting for transaction costs. This lack of a consistent ability to profit in the markets fits in well with the Odean (1998) theorization based on the expectations of the existence of overconfidence among traders accounting for at least some of the excessive volume in the markets (relative to economic requirements). Those who have learned to overcome their overconfidence (and/or other biases such as the disposition effect) will tend to benefit at the expense of those who have not, particularly in the case of zero/negative-sum markets where participants are in direct competition for returns.

4.2.4. Retail foreign exchange

The clear majority of the research into trader/investor activity and performance done thus far is concentrated on the equity markets. This is a function of that market's long history, relatively high levels of retail (individual) participation, and considerable volume of fundamental information, among other factors. Markets which are heavily professional – such as the heavily dealer-driven ones for government debt and foreign exchange – present significant hurdles both in terms of acquiring useful data from a decentralized market and the inclination toward privacy of those involved. Foreign exchange prices have received considerable research attention over the years in terms of valuation considerations (Mussa, 1979, Bacchetta and Wincoop, 2004, Froot and Ramadorai, 2005, Bacchetta and Wincoop, 2006, Berger et al., 2008, Berger et al., 2009), the forward discount puzzle (Baillie et al., 1983, Cumby, 1988, Cavaglia et al., 1994, Chaboud and Wright, 2005, Bacchetta and Wincoop, 2007, Burnside et al., 2009, Bacchetta and Wincoop, 2010, Baillie and Chang, 2011, Burnside et al., 2011b), the carry trade (Galati et al., 2007, Baillie and Chang, 2011, Burnside et al., 2011a, Menkhoff et al., 2012), and other pricing anomalies (Mussa, 1979, Goodhart, 1988, Froot and Thaler, 1990, Gourinchas and Tornell, 2004, Baillie and Chang, 2011). Similarly, a literature focusing on the microstructure of exchange rates and their trading has been developing for a number of years (Baillie and Bollerslev, 1991, Lyons, 1997, Lyons, 2001, Bacchetta and Wincoop, 2006, Sager and Taylor, 2006, Akram et al., 2008, Berger et al., 2008, Berger et al., 2009, Burnside et al., 2009, Osler et al., 2011, Mancini et al., 2012, Neely and Weller, 2013). The limited availability of usable transaction data, however, has largely confined work in the specific area of trader behaviour to theoretical and/or narrow scope efforts (Frankel and Froot, 1987, Frankel and Froot, 1990, Taylor and Allen, 1992, Ito et al., 1998, Osler, 1998, Payne, 2003, Menkhoff and Taylor, 2007, Bloomfield et al., 2009b, Neely et al., 2009, Kaltwasser, 2010, Neely and Weller, 2013).

Recently, however, the study of speculative activity has begun to expand into the retail foreign exchange market, which is a highly concentrated source of active market participation where data is starting to become available. As the use of the term "retail" suggests, this is a sector which is mainly the domain of individual traders. The study of individual market participants is nothing new in and of itself, as the stock market studies of behavioural effects mentioned earlier are also concentrated on individuals. The difference lies in the motivation of the participants. The activity of retail forex traders is almost exclusively short-term profit motivated, as noted in the broker CitiFX's trader survey findings (CitiFX, 2010a, CitiFX, 2010b) and discussed in Chapter 2.

The forex market at the individual level is also much more active in nature than is true of the equity markets (with perhaps the exception of day traders). As such, it allows for highly concentrated research on very active speculators – high frequency traders. What's more, retail forex is a zero/negative- sum market, which provides opportunities to directly observe relative speculator skill levels. Additionally, since exchange rates are notoriously hard to value,[42] forex fits the Kumar (2009a) model of a market where individuals are likely to exhibit strong behavioural biases, providing fertile ground for research into their decision-making.[43]

Retail foreign exchange trading has been available for a relatively short period of time, so data has only recently begun to be obtainable by researchers in a meaningful way. In some of the earliest research, Nolte and Voev (2011) use a month of data from one of the larger retail forex trading platforms to evaluate disposition effects among traders, while Simon and Heimer (2014) use data from retail foreign exchange traders to evaluate social network influences on performance, and (Heimer, 2013) evaluates the impact of leverage constraints on trader returns.

4.2.5. Overconfidence and increased trading activity

Odean (1998b) links overconfidence among investors to increased trading volume, and from there to reduced performance on the basis of investors failing to overcome the additional transaction costs incurred. The second part of that is explicitly tested in Barber and Odean (2000) based on the hypothesis that diminished performance in the form of lower relative returns at higher levels of trading activity indicates the presence of overconfident investors. This is accomplished using a large dataset of discount stock broker investor accounts. The authors find that while increased trading activity, measured in terms of account turnover, has little gross impact on investor returns, it does have an observable negative influence on net performance.

[42] See Meese and Rogoff (1983) for an oft-cited survey of exchange rate forecasting models.
[43] Chapter 2 of this thesis provides an overview of the retail foreign exchange market structure, its mechanics, and how it links to the sizeable global spot forex market. It also demonstrates the negative-sum nature of retail forex. Both the structure and the nature are important considerations when addressing research in this area. Additionally, Chapter 2 provides some insight into market participation – what motivates the traders and how they operate.

Thus, the conclusion is made that overconfidence drives excessive trading in the markets.

A shortcoming of the Barber and Odean (2000) analysis, however, is that despite having a large number of households in the study, the sample is heavily focused on relatively inactive investors.[44] The introduction of a dataset of retail foreign exchange traders, as will be employed herein, offers the opportunity to extend the research into a market where participants are much more active on average, providing considerably more opportunity to observe over-confidence driven decision-making.[45] The first test in this chapter is therefore to seek confirmation of the Barber and Odean (2000) findings whereby turnover is evaluated in relation to retail foreign exchange trader returns. The advantage of the dataset in use, as outlined in Chapter 3, is that it features a set of market participants who trade frequently, allowing for an extension of the link between overconfidence and trading activity not just in to the retail foreign exchange market, but to the active trader arena in general. The results for this initial analysis are presented in section 4.4.1.

4.2.6. Focusing on leverage

As noted in the previous section, turnover is the metric of investor activity favoured by Barber and Odean (2000). Turnover, however, is a composite measure comprising of two contributory elements in the form of transaction count and leverage use. This is something which can be demonstrated formulaically. To the extent that monthly turnover is simply the total amount of volume traded in a given month divided by the average account balance of the month in question, it can be expressed as:

$$Turnover_t = \sum_{i=1}^{n_t} Volume_{t,i} \Big/ AccountBalance_t \qquad (4.1)$$

where

$Turnover_t$ is turnover for month *t*

n_t is the number of trades for month *t*

[44] On average the households in question made only 4-5 trades per year. Even this figure likely distorts reality as it would take only a relatively few very active households (day traders) doing hundreds, if not thousands, of trade per year to inflate the sample mean.

[45] As indicated in Chapter 3, the traders in the employed dataset averaged holding positions about 1.5 days, with a median of 0.06 days.

$Volume_{i,t}$ is the volume for each trade *i* in month *t*

$AccountBalance_t$ is the average account balance for month *t*

Formula 4.1 can then be simplified:

$$Turnover_t = (Trades_t \times AverageVolume_t)/AccountBalance_t \quad (4.2)$$

where

$Trades_t$ is the total number of trades executed in month *t* (n_t above)

$AverageVolume_t$ is the mean volume of the trades made in month *t*

In Formula 4.2 trading activity is now expressed as a function of how many trades get executed and how large those trades are on average. The average trade size figure, however, also has two elements to it. One is the size of the account, which is a limiting factor constraining how large a position one can take. The other is the amount of leverage the trader employs in their trades. Leverage is simply a multiplier applied to one's account balance to get to a volume figure.[46] That means the turnover equation can be adjusted further:

$$Turnover_t = \frac{Trades_t \times (AverageLeverage_t \times AccountBalance_t)}{AccountBalance_t} \quad (4.3)$$

where

$AverageLeverage_t$ is the mean leverage ratio for trades executed in month *t*

This updated formula reflects the two decisions made by traders. One is how frequently they trade. The other is how much leverage they employ in the trades. If, as suggested in Section 4.2.2, there are contradictory explanations to the question of trade frequency, then it is reasonable to expect to see the number of trades executed by a trader in a given period be the less informative aspect of turnover by way of measuring overconfidence and/or sensation-seeking behaviour.

The corollary to trade frequency being the less informative contributor to turnover is that leverage employed must be the more meaningful of the two

[46] This makes leverage equivalent to turnover in terms of comparability across traders and period observations.

measures which combine into the determination of turnover. It makes intuitive sense from the perspective that overconfident traders will tend to trade larger positions in order to maximise their expected returns, while those simply learning may trade relatively small positions to minimize risk at a time when expected returns are lower, as suggested by Mahani and Bernhardt (2007) and Linnainmaa (2011).

This leads to the two initial hypotheses of this chapter.

Hypothesis 1: Higher levels of employed leverage are indicative of higher overconfidence and therefore correspond to lower returns

Hypothesis 2: Leverage is a better indicator of overconfidence than is trade frequency

These hypotheses are addressed in Section 4.4.2 and again in Sections 4.4.5 and 4.4.6.

4.2.7. The influence of trader experience and sophistication

Gervais and Odean (2001) suggest early-career investors are subject to overconfidence issues. It makes sense that as one spends more time in the markets – assuming they are not forced out – they will learn to overcome these issues and thereby produce better results. This is something which finds support in Nicolosi et al. (2009) and Seru et al. (2010), as both also link experience positively to performance. Feng and Seasholes (2005) specifically point to more experienced market participants suffering from less in the way of behavioural bias and also bring the idea of sophistication into the equation. To the extent that larger accounts are indicative of greater sophistication,[47] there too the expectation is to see a reduced impact from behavioural biases among those with higher capital levels. That is the finding of Nolte and Voev (2011) in looking at the disposition effect among retail forex traders.

This is where Barber and Odean (2000) run into a theoretical problem when attempting to judge overconfidence on the basis of performance linked back through activity level. If more experienced and/or more sophisticated traders do indeed show better returns then it suggests they are less active in the markets. Graham et al. (2009), however, find that more experienced

[47] Regulators have often used investor capital levels as at least theoretical indications of sophistication in the investment arena to determine things like disclosure requirements and participation suitability.

investors trade more frequently.[48] If the latter is true, then based on the Barber and Odean (2000) view, leverage use among this group of traders must be reduced to more than offset the higher number of trades to the point where turnover declines. Even if a disconnect between overall turnover and returns is allowed, leverage use will still be expected to drop on the basis of less influence from overconfidence.

That leads to the next two of the hypotheses tested in this chapter.

Hypothesis 3: There is a negative relationship between trader experience and leverage use (though positive with returns), but not necessarily with trade frequency.

Hypothesis 4: There is a negative relationship between trader sophistication and leverage use (positive with returns), but again not necessarily with trade frequency.

The results of testing these hypotheses are presented in Sections 4.4.3 and 4.4.4 respectively.

4.2.8. Changes in leverage use are uniformly significant

To the extent that experience and/or sophistication influence the amount of leverage employed by a trader, it must be accounted for when evaluating the implications for a given amount of leverage with regards to its implications for overconfidence. Stated simply, a certain level of average trade leverage will have different implications for an experienced trader and an inexperienced one, or for a more sophisticated trader and a less sophisticated one. The change in leverage, however, should remain significant in all cases. This leads to the final hypothesis of this chapter.

Hypothesis 5: Even when factoring in trader experience and sophistication, and other control factors, higher employed leverage signals more overconfidence, leading to lower returns.

The results of this testing is in Sections 4.4.5 and 4.4.6.

[48] This is theorized as being on the basis of a better-than-average type of overconfidence, as opposed to the miscalibration focus of Odean (1998b)

4.3. Data & Methodology

4.3.1. The data

The retail foreign exchange trader transaction and performance dataset described in Chapter 3 forms the basis for the empirical testing which follows. The 5502 active members with live trading accounts linked to the network with recorded trading activity and usable aggregated returns data provide just over 35,000 monthly observations as a starting point. To ensure data integrity, some adjustments need to be made which result in a fractional reduction of included members and data points. Since the primary focus of this chapter's analysis is at the monthly aggregate level, the first of these filters involves removing observations from May 2013 since only a handful of days are included from that month. The data thus starts with July 2008 and runs through April 2013.

The second screening is on the basis of leverage. The measure employed in this research is the average trade leverage used in Formula 4.3. This is calculated as the total USD-equivalent volume traded in a month divided by the USD-equivalent average daily account balance for that month. Thus, the leverage values are expressed as a per trade multiple of the trader's account balance, with a value <1 indicative of trades smaller than the average daily account balance for that month. Average trade leverage of more than 200 for any given month is quite rare.[49] The existence of any such data points in the set is more likely to indicate erroneous values than actual use of those levels of leverage (some are so high as to clearly be faulty, putting them all in question). In the case of members where half or more of their monthly observations feature these suspect leverage values (91 cases), the individual has been completely excluded. Where the number of suspect leverage values is less than half of a member's observations, those observations are excluded, but the remainder retained.

Because these excessively high leverage levels are judged to very likely be the result of calculations employing erroneous account balance readings (in this case, overly small), excluding them serves to avoid issues in the analysis of leverage and turnover, both which have account balance as the divisor in their

[49] I have heard of brokers allowing leverage of upwards of 500:1, but these were in the distinct minority and in areas of questionable regulatory oversight. Before the U.S. and other countries implemented leverage restrictions, 100:1 and 200:1 were the most seen levels of leverage permitted by brokers and remain such in domains where regulators have not instituted constraints.

calculations. Further, as account balance itself is a control variable in the models developed in Sections 4.4.5 and 4.4.6, excluding these observations also avoids potential outlier issues in that regard.

The above filtering brings the number of members in the study down to 5,357, and cuts the total number of observations to 34,002. Table 4.1 provides top level descriptive statistics for account balance and the trading activity metrics of note. Considerable skewness is apparent across the board, reflecting the heterogeneous nature of the members and their patterns of trading activity. Generally speaking, however, the sample comprises small traders. While the mean account balance is over $18,000 in USD-equivalent terms, the median is only $1,544. The prior research does not offer an indication of what to expect in terms of mean account balance, but King et al. (2012) do list a mean trade size of $68,000. On that basis, the network members would appear to be smaller than average accounts in that their mean trade size is only about $33,700. Lending support to this idea is that fact that more than half of the observations in the dataset come from those listing less than 3 years of experience.

Tables 4.2 and 4.3 bring some of the demographic values into consideration. The former includes descriptive statistics for trades, turnover, and return based on the different regional indications provided by members of the social network, while the latter does the same based on indicated experience. Noteworthy in Panel C of Table 4.2 is the considerably worse mean return for those members from the United States. The difference is highly statistically significant (t-value of 8.83). This aligns with a higher median monthly turnover value, but no real difference in trades/month. Similarly, Panel C of Table 4.3 shows a marked difference in mean returns between those with 0-3 years of experience and those with 3 or more. Here it can be observed that median turnover is higher for the less experienced group, but trade frequency is actually higher for the more experienced traders.[50]

The returns mentioned above are the combined member monthly returns described in Section 3.9 of Chapter 3 in which returns across all active accounts are merged on an account-balance weighted basis to derive a single value for

[50] In the aforementioned tables, and in the analysis in Section 4.4, the total number of trades registered for a given month is based on when a trade is entered. That then carries over to the average volume, monthly turnover, average duration, and average trade leverage values. Since more than 90% of trades are closed within a week, is unlikely there is any meaningful disconnect between return values, which are based on daily changes, and the activity measures.

those members with multiple active accounts. A second set of returns indicating relative performance is derived from this base set by determining a monthly aggregate unweighted mean return for all traders active in a given month and subtracting that from the return achieved by each individual. Table 4.4 presents the monthly average returns used to calculate the relative returns. Although the values are almost uniformly negative, there is considerable variation.

A third set of returns is calculated strictly on the basis of exchange rate changes, removing trade size (leverage) from the equation. In this series all trades are assumed to have a leverage of 1:1, meaning each trade's return is determined as if it had a value equal to the capital in the account at the time of entry. These trade returns are then summed (not compounded) for each month to provide a deleveraged cumulative monthly return. Because of the small returns of these trades,[51] the lack of compounding is unlikely to create any meaningful return distortion relative to any potential compounding effect there is in the actual returns. Likewise, since the vast majority of trades are short holding periods (more than 50% held less than 12 hours), not including the influence of interest carry is also unlikely to be problematic. As will be seen in Section 4.4, the variance between realized results and these deleverage returns is large enough that one need not be concerned by either compounding or interest carry in any case.

Additionally, in Section 4.3.6 below a variable is introduced which is the bid/ask spread return value. In order to derive a spread return value for a given trade, the estimated bid/ask spread value for the currency pair in question is divided by the exchange rate at which said trade was executed. For example, if a trader went long EUR/USD at 1.3000 with a spread estimate of 1.5 pips (0.00015) then the spread return would be estimated at -0.0115% (0.00015/1.3). Estimated trade bid/ask return values are then averaged across all trades done by a given trader in a given month on an equal weight basis.

These bid/ask spread estimates used in the above process are based on the snapshot values shown in Figures 3.12 and Figure 3.13 from Chapter 3. Unfortunately, the data needed to know the actual spread of a given exchange rate at the time a trade was entered is not available. Even if it was, however, there would still be a benefit to using a singular estimate value. The objective of

[51] The 25th to 75th percentile range of individual deleveraged trade returns is from -1.20% to +1.16%

the variable is to capture the composition of the different exchange rates traded by an individual – or at least the liquidity and volatility characteristics of them. If actual spreads were used in the construction of this variable, then any variance seen could be more reflective of different trading platforms, times of day, and other factors which influence the bid/ask spread experienced by a given trader for a specific trade.

4.3.2. The methodology

In Barber and Odean (2000) a quintile-based methodology is employed to compare investor performance across relative levels of trading activity. As noted above, portfolio turnover is the metric of choice for measuring trading activity. Performance results are expressed in both absolute and relative terms, with the authors using adjustments based on own-benchmark abnormal returns, market returns, CAPM, and Fama-French three-factor comparisons to provide additional depth to the analysis. This is the foundational basis for the analysis which follows.

For the purposes of this study, turnover is derived for each trader-month as the total USD-equivalent volume traded that month divided by the average USD-equivalent account balance (cash + open trade equity). Using average monthly balance allows the accounting for any deposits and/or withdrawals, interest carry, and the impact of trade performance on account value, which at times can be meaningful. Only days on which trading activity took place (to include the holding of open positions) are included in the average, which allows the results to reflect account balances during periods of decision-making.

In the foreign exchange market there is no market return, nor are there factors equivalent to Fama-French. This limits the ability to produce comparable benchmark return adjustments. Barber and Odean (2000) construct an own-performance benchmark based on the returns which would have been achieved had no portfolio change been made by a given investor. Since the focus is primarily on high frequency traders in this study, a reasonable assumption can be made for a baseline of no open positions at the start of each monthly period because any prior positions would have been closed. As such, if the trader in question makes no trades their return is zero, making the benchmark return zero.

In regards to the construction of the quintiles, these are done on a monthly basis. This allows traders to change quintile as they are more or less active from month-to-month. As such, the studies capture time-varying levels of potential trader overconfidence.

4.4. Analysis

4.4.1. The relationship between turnover and returns

The starting point for this analysis is replicating the primary Barber and Odean (2000) analysis to examine trader returns in relation to relative levels of trading activity, specifically using turnover as the metric. To accomplish this, each trader-month observation is assigned a quintile based on its relative ranking for that month. All observations are then aggregated by their quintiles to determine univariate mean values. Table 4.5 provides the descriptive statistics for the quintiles, plus statistics on the variation from quintile to quintile and between the least active and most active quintiles (Q1 vs Q5).

Consistent with prior findings in the literature, the Table 4.5 results support the idea that higher levels of turnover equate to worse performance, both in absolute terms and in relative ones. The difference in return between the first and second quintiles is not significant (-1.00% vs -1.34%), but it quickly becomes so between the subsequent quintiles. In particular, the 5th quintile shows a dramatic worsening of returns (-17.62%), though given the skewness of the data, this is at least partly reflective of a wide dispersion of values in that highest category.

Aside from the general turnover/returns relationship linkage in the data, one other potentially very significant item is worth noting. The average balance values decline noticeably across the turnover quintiles. The smallest accounts are thus the ones trading relatively most actively. Trade frequency rises with turnover, and trade duration falls correspondingly, which both fit the expectation that higher turnover is often (but not only) driven by more frequent trading and that more active traders tend to operate in relatively shorter time frames. The volume indications increase with turnover, as does average leverage, which are both to be expected.

As outlined in Section 4.1, turnover can be broken down into two decisions – trade frequency and leverage. It is noted in Section 4.1.2 that trade frequency can be influenced by potentially conflicting factors which are not necessarily linked to overconfidence. While trading more in the negative-sum retail forex market has a direct mathematical influence on returns, if trade frequency is not such a clean indication of overconfidence, then there should not be as much of an impact on returns when looking at that metric.

Table 4.6 provides descriptive statistics based on that question in Panel A. The same quintile methodology is employed as was done using above, replacing turnover with monthly trades (trade frequency). As is the case with turnover, and as expected mechanically, rankings based on trade frequency also show that more activity relates negatively to trader performance. The pattern of worse returns as trading activity increases holds, though not as strongly as in the case of turnover. The inter-quintile differences in return are not as large, nor are they as statistically significant.

Interestingly, however, the first four quintiles defined in trade frequency terms show worse performance than what is seen in terms of turnover (-3.92% to -6.99% as compared to -1.00% to -6.27%). The relative underperformance is reversed dramatically in the fifth quintile, however (-8.75% vs. -17.62%). This is true for both absolute and relative returns. At least at this aggregate level, trade frequency does have a relationship to trader returns. That said, the influence is not as strong relative to turnover amongst the most active traders where one would expect to see the highest levels of overconfidence-driven trading.

Worth observing in Table 4.6 is the reverse account balance pattern noted in Table 4.5. Here higher levels of trade frequency are associated with larger accounts. So between the two sets of results there is a pattern of larger traders, which are presumably more sophisticated, trading more frequently, but at lower levels of turnover. The implication there is one of lower leverage. This will be revisited in Section 4.4.4.

4.4.2. The relationships between leverage and returns

The observation of the relationship between trade frequency and returns in Table 4.6 brings up the first primary hypothesis – whether leverage is a stronger indication of overconfidence in traders than trade frequency. Continuing with the established methodology, the data is now quintiled on the basis of average trade leverage. Panel B of Table 4.6 provides descriptive statistics based on this segmentation. The immediate observation is how close both the return and relative return values for the quintiles based on average leverage are to those based on turnover shown in Table 4.5. Statistically, there is no significant difference (except in the first quintile), indicating a very close relationship between turnover and average trade leverage. It is worth noting as well the dramatic decline in average account balance across the leverage quintiles, confirming the suggestion above that it is smaller – presumably less sophisticated – traders who operate at the highest levels of leverage and thus theoretically with the greatest degree of overconfidence.

The influence of leverage on returns can be examined in another way as well. Hypothetical deleveraged returns may be used in the place of actual realized returns to strip out the influence of the trade size decision on performance. As noted in Section 4.2.1, deleveraged returns are calculated as the cumulative return of all trades entered in a month assuming that each trade is done at 1:1 leverage, thus just accounting for the exchange rates movements captured (market timing). By removing the influence of the leverage decision in returns what is left is an evaluation of the combination of skill (or luck) in the directional trading of exchange rates, plus the bid/ask spread cost.

The results of this deleveraging of returns shown in Panel A of Table 4.7 are informative. When looking at the turnover quintiles, over the first three quintiles there is effectively no pattern to the results. It isn't until Quintiles 4 and 5 (-1.04% and -2.67%) that the expected pattern emerges. The same can be said for the quintiles ranked on trade frequency. In both cases, however, the influence of leverage on trading performance can be seen clearly in the differential between the deleveraged returns and the realized returns for the same quintiles from the prior tables. This is particularly so at the higher levels of trading activity. For example, for turnover the difference between the 5th quintile actual returns and the hypothetical deleveraged one is nearly 15% (1495bp).

That said, it is reasonable to expect lower returns on the basis of higher trade frequency as a simple mathematical expression of the negative sum nature of retail forex trading. More trades means greater cumulative spread costs. And since trade frequency is an element of turnover, it is reasonable to expect higher turnover to produce lower returns as well. Thus the really informative aspect of Table 4.7 is the deleveraged returns of the quintiles derived on the basis of average trade leverage. They show no statistically significant pattern. The fifth quintile return (-0.77%) is markedly lower than the first quartile one (0.77%), but it is actually the second quintile which shows the worst return level (-1.18%).

On the face of it, that lack of a pattern in performance for the deleveraged returns is problematic. After all, if leverage use is supposed to be indicative of impaired trading performance, the deleveraged return values should be trending lower as one increases in quintile ranking. This is where revisiting the patterns of trade frequency is required. Referring back to Panel B of Table 4.6, a clear pattern of decreasing trade frequency as leverage is increased can be seen. That needs to be taken into consideration.

Panel B of Table 4.7 accomplishes this using the average trades per month for each quintile across the three measures of trading activity to create an average deleveraged return per trade. This is where the importance of leverage as an indication of overconfidence becomes clearest. Leverage is the only one of the three activity measures for which average returns worsen progressively from lowest quintile to highest – going from 0.002% in the first quintile to -0.023% in the fifth. In the case of trade frequency, the pattern is exactly the opposite (-0.105% in the first quintile, -0.007% in the fifth), indicating that higher levels of activity are indicative of better (albeit still unprofitable) traders. Turnover shows up and down readings, likely as a result of the mixed influence of trade frequency and leverage use on that metric.

High use of leverage is therefore not only bad in terms of its influence on realized returns because it exacerbates an already negative return expectation, per what is seen in Table 4.6. It is an indication of an overconfident trader making worse trades, as per the suggestions of Kahneman and Riepe (1998) and Burks et al. (2013). This makes it a better indication of overconfidence than either turnover or trade frequency.

These results thus provide support for Hypothesis 1in showing that increased leverage use, to the extent that it indicates increased overconfidence, corresponds to lower returns – both in aggregate and in terms of market timing. These results also support Hypothesis 2 that leverage use is a better indication of overconfidence than is trade frequency.

4.4.3. The impact of experience on overconfidence

To confirm the impact of overconfidence on trading activity, the introduction of factors which should have an influence on overconfident trading is required. Trader experience, as noted in section 4.1.3, is just such a factor. That data is available in the dataset, which allows for testing Hypothesis 3 regarding the link between experience and the application of leverage by using categories based on trader experience. Table 4.8 presents descriptive statistics for the dataset divided on the basis of indicated years of trading experience. It should be noted that no adjustments are made in trader classification based on the amount of time a trader is in the network. The experience indications are applied directly as provided for all months where a trader was active.

The results shown in Table 4.8 indicate that more experienced traders are better performers, as is expected. There is a clear, and statistically significant, difference between the realized returns of those with 0-3 years of experience and those with more (t-value 13.93). Importantly, the difference between realized and deleveraged returns for the more experienced traders is markedly lower than it is for less experienced ones, and more experienced traders use lower levels of leverage as well. There is thus evidence in support of the idea that experienced traders are less influenced by overconfidence as indicated by their application of leverage.

It should be observed that Table 4.8 shows more experienced traders tend to have larger accounts. They actually do not trade at lower levels of turnover, however. If anything, they turn their accounts over more frequently than their less experienced peers. While the experienced traders do use less leverage, on average, they tend to trade much more frequently. This is noteworthy both because it highlights the trade frequency concerns brought up in Section 4.1.2, and because their higher trade frequency is not matched by lower deleveraged returns. That suggests they are skilled enough to overcome the influence of the extra spread costs. In other words, their trade expected returns are far better than those of their less experienced peers, even when removing leverage from the equation, indicating a lesser influence from overconfidence driven trading, as is expected. Thus, support is found for Hypothesis 3 both in terms of experienced individuals using less leverage, but not necessarily expressing their lower general level of overconfidence via less frequent trading.

4.4.4. Sophistication and overconfidence

Sophistication is another factor which may influence the impact of behavioural biases like overconfidence on trading activity, and by extension returns, as suggested by Hypothesis 4. If one considers the size of a trader's account as an indication of their level of sophistication, which is a common regulatory standard backed up by retail aggregator research linking account size to returns (Wagner and Shea, 2011), then a test of this hypothesis is possible. The results shown in Table 4.8 and in prior tables already provide an indication of links between account size, trading activity, and trading performance. Table 4.9 does so more explicitly by returning to the quintile methodology. In doing so it is seen that traders with larger accounts tend to trade at lower turnover levels (811 for the first quintile vs. 219 for the fifth). This is driven by significantly lower levels of leverage rather than by less frequent trading, as the pattern is actually that larger accounts trade more often than smaller ones. Leverage use drops from 30 in the first quintile to 3 in the fifth, while trade frequency rises from 38 to 166 respectively.

On the performance side of things, the expected pattern whereby larger accounts experience better returns is clearly seen, as they improve from -12.85% in the first quintile to -0.83% in the fifth. Further, the spread between realized and hypothetical deleveraged returns is significantly narrower for larger accounts than for smaller ones, indicating the reduced influence of leverage on performance for larger traders. This provides additional support for the idea that sophistication, as measured by account size, is a factor in the influence of overconfidence on trading activity and performance. Further, the fact that bigger traders are more active means they are better performers on a per-trade basis, supporting the argument that there is less influence from overconfidence as account size rises. As is the case with experience, then, Hypothesis 4 is supported from the perspective of sophisticated traders using less leverage, as well as in terms of trade frequency not necessarily being negatively linked.

4.4.5. A model of trader returns

Hypothesis 5 proposes that even when controlling for experience and sophistication, as well as other factors, higher leverage use leads to worse monthly returns. The previous sections provide the basis for developing a model of trader monthly returns based on leverage and trade frequency as measures of trading activity, along with experience and trader sophistication to test this idea. As noted in Section 4.2.1, there is also an indication that traders from the United States underperform their peers from other regions, which suggests value in including geographic region as an additional control variable.

This leads to the following base model:

$$
\begin{aligned}
Return_{i,t} = \alpha + \beta_1 Leverage_{i,t} + \beta_2 Balance_{i,t} \\
+ \beta_3 Trades_{i,t} + \beta_4 Region_i \\
+ \beta_5 Inexperienced_i + u_{i,t}
\end{aligned}
\tag{4.4}
$$

Where

$Return_{i,t}$ is the return of Trader *i* in month *t*.

$Leverage_{i,t}$ is the log of trade leverage of positions entered by Trader *i* in month *t*.

$Inexperienced_i$ is a dummy for indicated experience of Trader *i* (3 years or less = 1).

$Balance_{i,t}$ is the log of the avg. account balance of Trader *i* in month *t*.

$Trades_{i,t}$ is the log of the number of trades done by Trader *i* in month *t*.

$Region_i$ is a dummy for the global region of Trader *i* (United States = 1).

As noted in Section 4.1.2, the *Balance*, *Leverage*, and *Trades* variables have considerable positive skewness to them. A log transformation to those values is therefore applied to minimize the potential for distortions from observations well into the tail of the distribution. This also serves in the case of the *Balance* to rescale the coefficient values to more observable levels. To further reduce the potential impact of outlier observations, the three variables are winsorized at the 1% and 99% levels, as is the *Return* dependant variable. Additionally, since trader-months lacking an entry for either experience or geographic region are of no use in this analysis, they are excluded. As the number of months included for members varies considerably, the result is an unbalanced panel dataset with a starting observation count just over 28,000 from 4046 individuals.

Table 4.13 provides descriptive statistics for this sub-sample for the purposes of comparison to the full sample. They indicate that the sub-sample features somewhat smaller accounts ($15,552 average/ $1,199 median vs. $18,017 average/$1,544 median). The sub-sample also has more observations from inexperienced members (63.76% vs. 54.96%) and from US-based traders (40.19% vs. 33.27%). Not surprisingly given the results described in the last two sections, this results in an increase in the mean monthly turnover (522 vs 492) and leverage (13.52 vs 12.81) values, but has little impact on trade frequency (78 vs. 80). Monthly returns for the sub-sample group are slightly lower as well (-5.96% vs. -5.88%). Overall, though, the sub-sample does not represent a radical departure from the broader one. Additionally, since controls for both account size and experience level are part of the model developed below in equation 4.5, the sample composition shift is not bothersome.

Table 4.10 provides a set of variable correlations for the sub-sample. Not surprisingly, average trade returns are positively correlated to monthly returns (0.27). Leverage is negatively correlated to monthly returns (-0.23), but in line with the above results that relationship is much less significant for trade frequency (-0.06). All of these correlations are based on log values, so there is not a question of relative comparisons in this case. The strongest correlation is between leverage and account balance (-0.58), which falls in line with the results seen in section 4.4.4 above. Leverage is also negatively correlated with trade frequency (-0.25) and trade duration (-0.24). In the latter case that most likely reflects smaller relative positions sizes being taken in the face of the prospect of greater nominal price volatility while holding positions for longer periods of time. In the former case, it may reflect holding a general level of risk constant as one increases trade frequency. As seen in the experience and sophistication analysis, however, other factors may be at work there.

An ordinary least squares (OLS) regression is employed to test Hypothesis 5, with clustering on member ID to account for correlation of residuals at the individual trader level based on potential unobserved and otherwise uncontrolled for heterogeneity between the traders in the sample. Robust standard errors are employed to account for the presence of heteroscedasticity and non-normality in the random variables. To account for general market conditions, the model also controls for time (e.g. monthly) fixed effects.[52] The regression results are presented in Table 4.11. Based on the earlier findings, the expectation is to see a negative coefficient for the *Leverage* and *Trades* variables, as well as for the *Inexperienced* and *Region* dummies

[52] This is done by creating a dummy variable for each month of the study, starting at 1 for the first month in the study period (July 2008) running to 58 for the final month (April 2013).

since both are set to reflect negative contributors to performance (less experienced and U.S.-based trading). The coefficient for the *Balance* variable, however, should be positive.

The first five columns shown in the table list the result of single independent variable regressions including all of the factors just outlined – *Leverage*, *Trades*, *Balance*, *Inexperienced*, and *Region*. The sixth and seventh columns first combine the three random variables and then add the *Region* and Ine*xperienced* dummies in as well. In all tests, the coefficient signs meet expectations – *Leverage*, *Trades*, *Experience*, and *Region* are all negative, with *Balance* positive. Further, the coefficients are economically meaningful across the board. For example, a 10% increase in average trade leverage equates to an expected reduction of 0.36 percentage points (36bp) in monthly returns per the first column results.

Noteworthy from the sixth column is the reduction of the coefficient values for *Leverage* (-0.0342 vs -0.0372) and *Balance* (0.0119) vs. 0.0216) and the rise for *Trades* (-0.235 vs. -0.109). The addition of *Balance* and *Trades* are actually having mostly *offsetting* effects on the Leverage coefficient. Combining *Leverage* and *Trades* leads to both coefficients being more negative and more significant (-0.041 and -0.019 respectively, though unpublished), but adding in *Balance* has a modest offsetting effect for leverage, which fits with both the developed expectations and the strong negative correlation just noted. While both *Inexperience* and *Region* are negative and both statistically and economically significant in the seventh column results, they have very little impact on the coefficients for the random variables.

To strengthen the analysis, an additional regression is run which adds in three elements. The first addition is a set of member dummies to account for individual trader characteristics not otherwise captured in the model, which means dropping the time-invariant *Region* and *Inexperienced* dummies. The second element is looking at only those members with at least 10 months of data, to limit potential outlier effects of those individuals with few monthly observations. This narrows the focus to 1,008 individuals covering 18,238 total trader-month observations.

The last introduction to the analysis is two new control variables. One is the average holding period (duration) of trades to account for any changes from month to month in the amount of time a trader spends in the market per trade.

This might reflect a change in trading style or methodology. The other is the mean bid/ask spread return for trades done in a given month (always negative) mentioned in Section 4.2.1. Since the bid/ask spread tends to reflect the liquidity and volatility level of a given exchange rate, it can be viewed as a proxy for trade risk from at least the perspective of the price volatility of the instrument(s) being traded. As such, the mean value for a given month indicates the relative composition of the riskiness of the exchange rates in which one trades, weighted by trade frequency. Including this spread return therefore provides a risk control variable such that higher (less negative) values indicate less risk, while lower (more negative) values point to greater risk.

Adding the *Spread* and *Duration* control variables and dropping the two dummy variables adjusts the base model from Equation 4.4 as follows.

$$Return_{i,t} = \alpha + \beta_1 Leverage_{i,t} + \beta_2 Balance_{i,t} + \beta_3 Trades_{i,t} + \beta_4 Spread_{i,t} + \beta_5 Duration_{i,t} + u_{tm} \tag{4.5}$$

Where

$Spread_{i,t}$ is the mean estimated bid/ask spread of trades done by Trader *i* in month *t* expressed as a negative return.

$Duration_{i,t}$ is the log of the mean duration (in days) of trades done by Trader *i* in month *t*.

Remaining variables as previously defined.

The results of this new model can be seen in the first column of Table 4.12, again based on a member-clustered OLS regression with robust standard errors. The incorporation of the member fixed effects markedly increases model fitness as measured by the adjusted R^2, but neither that nor the additional control variables have a notable impact on the two primary variables of interest – *Leverage* and *Trades*. The coefficients for both remain negative and highly significant, and if anything they are a fraction stronger. Thus, the general findings remain.

4.4.6. A model of overconfident trader performance

As discussed in Section 4.4.2, it is insufficient to only analyse realized returns when attempting to properly judge the impact of overconfidence on trading performance when working in the context of a negative sum market. Yes, more frequent trading and higher leverage use are shown in the model developed in Section 4.4.5 above to negatively impact on monthly returns, but this is only to be expected. If the idea of overconfidence driven trading is that performance is impaired by doing poor trades, then it should be possible to develop a model which demonstrates this on a per trade basis. As such, the following can be proposed:

$$\begin{aligned} AverageDeleveragedReturn_{i,t} \\ = \alpha + \beta_1 Leverage_{i,t} + \beta_2 Balance_{i,t} + \beta_3 Trades_{i,t} \\ + \beta_4 Spread_{i,t} + \beta_5 Duration_{i,t} + u_{tm} \end{aligned} \quad (4.6)$$

Where

$AverageDeleveragedReturn_{i,t}$ is the mean exchange rate change captured by each trade for Trader i in month *t* (inclusive of spread).

Remaining variables as previously defined.

Equation 4.6 simply re-expresses Equation 4.5 to allow analysis at the trade level to see whether leverage use and/or trade frequency are contributory factors to performance. Results for running the equivalent member-clustered OLS regression with month and member fixed effects can be found in the second column of values in Table 4.12. As is the case previously, the expectation is for both *Leverage* and *Trades* to be negative and significant if they each signal overconfident trading. The reality is that only in the case of *Leverage* (-0.00015) does that hold in the results, however. The coefficient for *Trades* is actually positive and significant at the 99% confidence level (0.00013). Thus, increased leverage use is related to diminished market timing performance, while the opposite is true for increased trade frequency.

The results of this final test thus confirms the findings of Section 4.4.2 in showing the existence of a negative relationship between leverage and trader performance which goes beyond simple monthly returns and looks into an overconfident trader's performance on a per trade basis. They also show that trade frequency does not do a good job of serving in the same capacity for these active traders. As such, Hypothesis 5, the primary hypothesis of this chapter, is supported. Increased leverage is a better indication of overconfidence than is increased trade frequency.

4.4.7. Robustness checks

There are a number of decision points with regards to the data preparation and analysis done in this chapter which could be seen as having an influence on the findings. Some are addressed above. Here are others of note.

First, a secondary analysis to that from in Section 4.4.1 may be performed in which members are assigned to fixed, rather than potentially fluctuating turnover quintiles (and by extension trades and leverage). This is accomplished by aggregating each member's data across all of their active months, then placing them in a quintile based on their ranking relative to all members from that perspective. This serves to hold member classification fixed across all observation periods, which allows for analysis on the basis of the traders' general behaviour rather than activity which may be reflective of monthly vagaries. The pattern of returns derived from these alternative quintiles remains unchanged, however.

Second, re-running the first three and sixth regressions from Table 4.11 (leverage; balance; trades; plus leverage, balance, and trades combined) on the full 5,357 member sample set produces coefficient values and significance indications little changed from the 4,046 sub-sample presented in the table. Incorporating "style" dummies based on the member profile indication of approach as described in Chapter 2 (technical, fundamental, momentum, news, none) fails to improve model fitness or otherwise change the results. Additionally, running the average return regression from Table 4.12 without member fixed effects has no meaningful effect on the results. Similarly, expanding the regression to include the full 4,046 member sub-sample has virtually no impact on either the coefficients or the significance of the results. These findings are not published.

Finally, as an alternative to the OLS methodology employed, a secondary set of panel regressions were run based on Equations 4.5 and 4.6. They were developed with member ID employed as the entity (panel) and the previously defined *Month* included as the time variable (see Footnote 52). Because members varied in terms of the amount of time they were in the dataset, as well as when they first appeared, the result was an unbalanced panel. A Hausman test indicated that a fixed effects (within) regression estimator was favoured over using a generalized least squares (GLS) random effects estimator. This fits with the general idea of heterogeneity among traders influencing their returns, which is seen in comparing the Table 4.11 results from Column 7 to those from the Monthly Return column in Table 4.12 where adding in the member fixed effects markedly improved model fitness, as measured by Adjusted R^2. Running the fixed effects panel regression with robust standard errors produced more significant results than was the case with the OLS version. The decision to focus on the latter in the results presented herein was made on the basis of selecting the more conservative option.

4.5. Further Discussion & Concluding Remarks

The results of the tests performed in this chapter confirm the performance shortcomings of retail investors and traders, particularly when considered from the perspective of monthly returns. This is especially so in the context of a negative sum market such as retail foreign exchange. After all, if individual traders are not generally winners anyway, adding increased trading activity in one fashion or another will only make things worse.

The key in really being able to identify overconfident behaviour among traders is looking at results even when accounting for the nature of the underlying market. Barber and Odean (2000) are able to do this through the use of benchmarking, but in retail forex that option is not readily available. An alternative approach is required, which in this chapter has been to shift the focus from overall returns to per trade performance. Doing so provides a way to gauge whether the proposed indications of overconfident trading – higher trade frequency and increased leverage as sub-components of increased monthly turnover – are, in fact, indicative of overconfident traders making worse decisions and/or exchange rate forecasts. The results presented in the prior sections suggest that this is indeed the case. Overconfident traders do not simply suffer lower returns because of the cost of the added trades, but because they make worse trades in the process.

Noteworthy in the results of this analysis is that the influence of overconfidence can be seen even when accounting for trader experience and sophistication. As traders mature, and presumably gain skill, they do perform better, as indicated in Tables 4.8 and 4.9 and in the signs of the *Inexperienced* and *Balance* regression coefficients from Table 4.11. It is hypothesized that trading maturity leads to the reduction of the influence of behavioural biases.

The analysis herein provides general support for that idea. There is little doubt that overconfidence, as expressed in the form of using excessive leverage, has a negative impact on returns. Clearly, though, more experienced and sophisticated traders simply are not as prone to falling into that trap as their newer, less sophisticated peers.

The analysis does offer some interesting areas for potential further research, though. One is the need to look closer at account balance. It is used here as an indication of trader sophistication, and certainly there is a link between larger accounts and better performance as hypothesized (at least in terms of monthly returns). Importantly, however, there is an even stronger correlation between leverage and account balance (negative in this case), as indicated in Table 4.10. This introduces the question whether there is a risk aversion effect which happens as traders work with larger accounts – or perhaps increased risk seeking in those with smaller accounts. Restating in terms of a research question, would increasing the size of a trader's account by adding in additional funds (or withdrawing them) impact the amount of leverage they employ in their trades? Alternatively, is the performance of larger accounts not necessarily an indication of sophistication, but rather of risk aversion – or perhaps some combination of the two?

This question relates to a potential issue in using leverage use as a metric for overconfidence (and necessarily turnover as well). Is increased leverage use really a function of overconfidence? Or is it just a change in an investor's desired level of risk? The two are not mutually exclusive. One could increase position size (leverage) because of an excess of confidence in their market timing ability and/or in order to increase their general level of risk-taking.

In the context of this research, two elements tend to keep the focus on overconfidence rather than changing risk appetite, however. The primary one is the observation of changes in market timing performance. If it were simply a question of changing one's risk level via leverage adjustment, there would not be an expected impact on monthly returns based on position size changes. There is no inherent reason to expect a change in market timing performance as measured by deleveraged returns. Secondarily, the regressions in Table 4.12 control for at least one aspect of an investor's risk level by incorporating instrument selection into the model.

The experience angle is one also worth looking at more closely. Here a relatively arbitrary cut-off is made based on the way the social network phrased its profile question and because of how the performance figures divided in the descriptive statistics. No accounting is made for how much additional experience traders gained from the time they entered their profile information (along with the assumption being made that they did not change it along the way). Further, simple calendar time in the market is presumably not the same as active trading experience, so it is worth exploring how much actual trading has been done rather than use some time metric. The research question could be whether less overconfidence is exhibited by those who have made more trades, not just by those who have been in the markets for more months or years. Unfortunately, the dataset employed here is insufficient to the task.

Another open question from this analysis is the reason why non-US traders significantly outperform US-based traders. Any number of potential influencing factors come to mind and could be explored. Of course the analysis presented here is based on aggregates. Cross-sectional analysis of different types of market participants is worth pursuing to evaluate more specifically the differences in behaviour and decision-making between groups of traders (some of which is done in Chapters 5 and 6).

Taken as a whole, this chapter demonstrates that the portfolio turnover metric often used to assess relative levels of trading activity with regards to measuring overconfidence should be broken down into the component parts of trade frequency and leverage for more specific and informative analysis. The results suggests that leverage is in fact the better of the two components when it comes to observing overconfident trading in the markets, likely due to the impact of learning and other influences on trade frequency which could lead to higher levels of trading than would otherwise be expected – or even the simple fact of positive expectancy traders rationally attempting to maximise returns.

Table 4.1

Descriptive Statistics on Account Balances, Trade Frequency, Transaction Volume, Turnover, Return, Trade Holding Period, and Trade Leverage with Inexperienced and Regional Proportions

Sample of 5,357 retail aggregator based foreign exchange traders for the period July 2008 to April 2013 comprising 34,002 trader-months of observations (one trader-month being the performance of one individual in a single month). All results are based on aggregated values for traders with multiple accounts (where applicable), with monthly returns derived using a weighting based on capital balances for included accounts. Returns are based on the compounded daily returns calculated by the social network platform (when trading activity took place). Daily Capital Balance and Trade Volume values are USD-equivalent based on prevailing exchange rates on the measurement dates. Trades indicates the number of completed round-turn positions, with trades counting in the month they were initiated in the case of positions which overlap months. Turnover is calculated as total volume traded in a month divided by the average daily balance. Trade Duration is the average position holding period (open to close) for round-turn trades initiated in a month, measured in days. Trade Leverage is the average size of the trades initiated in a month relative to the account balance (volume/balance), expressed as a multiple of the account balance. Inexperienced indicates the proportion of observations which are from traders listing 0-3 years experience in their member profile. Region = US indicates the proportion of observations which are from traders listing United States as their geographic home region in their member profile.

	Mean	**25th Percent.**	**Median**	**75th Percent.**	**Standard Deviation**
Daily Capital Balance ($)	18,017	348	1,544	6,077	122,580
Trades	80	6	22	67	329
Trade Volume ($)	33,706	1,583	6,753	18,481	160,135
Turnover (X:1)	492	25	104	371	3242
Return	-5.88%	-15.29%	-1.73%	3.51%	30.74%
Trade Duration (days)	3.82	0.11	0.46	1.70	21.15
Trade Leverage (X:1)	12.81	1.44	4.77	13.93	22.45
Inexperienced	0.5496				
Region = US	0.3327				

Table 4.2

Descriptive Statistics of Trading Activity and Performance Based on Data Provided in User Profiles – Geographic Region

Sample of 5,357 retail aggregator based foreign exchange traders for the period July 2008 to April 2013 comprising 34,002 trader-months of observations (one trader-month being the performance of one individual in a single month). Traders provided a broad geographic indication as part of their profile information. Only Asia/Pacific, Europe, and United States were offered as options, with some members making no selection. Panel A compares trade frequency, Panel B turnover, and Panel C returns. Observations are trader-months for all traders in a given category. Most noteworthy is the relative underperformance of United States traders in returns. While Europe and Asia/Pacific are not statistically significantly different, the United States traders are significantly worse at the 99% confidence level than those from both other regions.

Panel A: Monthly Trades	**Mean**	**25th Percent.**	**Median**	**75th Percent.**	**Standard Deviation**	**Observ.**
Asia/Pacific	80	7	25	75	206	5,657
Europe	78	7	23	65	211	11,178
United States	77	6	22	63	437	11,311
No Entry	90	5	20	68	367	5,856

Panel B: Monthly Turnover	**Mean**	**25th Percent.**	**Median**	**75th Percent.**	**Standard Deviation**	**Observ.**
Asia/Pacific	458	29	108	375	1,438	5,657
Europe	545	27	107	375	4,806	11,178
United States	531	29	121	414	2,675	11,311
No Entry	350	13	70	276	1,041	5,856

Panel C: Monthly Returns	**Mean**	**25th Percent.**	**Median**	**75th Percent.**	**Standard Deviation**	**Observ.**
Asia/Pacific	-4.82%	-15.21%	-1.44%	4.47%	35.00%	5,657
Europe	-4.47%	-13.46%	-1.20%	4.25%	30.42%	11,178
United States	-7.96%	-18.62%	-2.67%	2.52%	29.38%	11,311
No Entry	-5.58%	-12.45%	-1.49%	3.28%	29.28%	5,856

Table 4.3

Descriptive Statistics of Trading Activity and Performance Based on Data Provided in User Profiles – Experience

Sample of 5,357 retail aggregator based foreign exchange traders for the period July 2008 to April 2013 comprising 34,002 trader-months of observations (one trader-month being the performance of one individual in a single month). Traders provided an experience indication as part of their profile information, with four potential options: 0-1 years, 1-3 years, 3-5 years, and 5 or more years. Entries were lacking in some cases. Panel A compares trade frequency, Panel B turnover, and Panel C returns. Observations are trader-months for all traders in a given category. Noteworthy is the pattern of higher trade frequency with greater experience show in Panel A. Perhaps most meaningful is the split shown in Panel C in the performance of traders with less than or greater than 3 years of experience. The difference in mean return values are significant at the 99% confidence level.

Panel A: Monthly Trades	**Mean**	**25th Percentile**	**Median**	**75th Percentile**	**Standard Deviation**	**Observ.**
0-1 years	51	5	17	46	151	6,471
1-3 years	76	6	21	64	415	12,218
3-5 years	87	8	27	75	251	3,644
5+ years	112	11	34	98	317	7,245
No Entry	79	4	17	59	324	4,424

Panel B: Monthly Turnover	**Mean**	**25th Percentile**	**Median**	**75th Percentile**	**Standard Deviation**	**Observ.**
0-1 years	503	29	122	422	2889	6,471
1-3 years	488	28	116	411	1723	12,218
3-5 years	484	28	108	356	3123	3,644
5+ years	599	30	105	353	5591	7,245
No Entry	321	9	53	226	1039	4,424

Panel C: Monthly Returns	**Mean**	**25th Percentile**	**Median**	**75th Percentile**	**Standard Deviation**	**Observ.**
0-1 years	-9.02%	-21.24%	-3.61%	1.75%	32.04%	6,471
1-3 years	-7.11%	-17.61%	-2.47%	3.22%	31.37%	12,218
3-5 years	-2.78%	-11.67%	-0.68%	5.01%	31.44%	3,644
5+ years	-2.50%	-9.40%	-0.26%	5.10%	28.32%	7,245
No Entry	-6.00%	-13.09%	-1.94%	2.51%	29.49%	4,424

Table 4.4
Monthly Aggregate Member Mean Returns

Sample of 5,357 retail aggregator based foreign exchange traders for the period July 2008 to April 2013 comprising 34,002 trader-months of observations (one trader-month being the performance of one individual in a single month). Returns presented are the average actualized returns (inclusive of spread) for all traders active in a given month.

Month	Active Members	Avg. Return	Month	Active Members	Avg. Return
July-08	27	-6.40%	December-10	1,054	-7.91%
August-08	23	-20.03%	January-11	1,069	-7.65%
September-08	21	-9.66%	February-11	1,089	-4.75%
October-08	18	-5.34%	March-11	1,019	-8.55%
November-08	20	-1.99%	April-11	1,008	-7.36%
December-08	22	-7.91%	May-11	914	-7.69%
January-09	28	-5.17%	June-11	852	-6.02%
February-09	31	-0.93%	July-11	848	-6.13%
March-09	30	-15.39%	August-11	823	-6.11%
April-09	38	0.08%	September-11	829	-5.55%
May-09	40	-10.47%	October-11	766	-4.42%
June-09	42	-0.60%	November-11	783	-2.07%
July-09	44	-6.14%	December-11	771	-2.21%
August-09	55	0.64%	January-12	839	-7.07%
September-09	52	-4.71%	February-12	854	-5.52%
October-09	49	-4.63%	March-12	848	-1.24%
November-09	56	-6.41%	April-12	863	-3.94%
December-09	87	-5.66%	May-12	888	-6.90%
January-10	109	-5.04%	June-12	799	-2.51%
February-10	329	-8.83%	July-12	832	-2.90%
March-10	538	-9.17%	August-12	793	-5.16%
April-10	697	-5.96%	September-12	774	-4.16%
May-10	806	-6.98%	October-12	811	-3.99%
June-10	917	-8.16%	November-12	740	-2.44%
July-10	1,038	-9.73%	December-12	666	-7.17%
August-10	1,062	-9.32%	January-13	782	-8.14%
September-10	1,081	-10.91%	February-13	803	2.31%
October-10	1,104	-8.62%	March-13	772	-4.60%
November-10	1,032	-4.55%	April-13	717	-3.11%
				Average:	**-5.88%**

Table 4.5

Descriptive Statistics for Returns and Relative Returns for Trader Quintiles Formed on Monthly Turnover

Sample of 5,357 retail aggregator based foreign exchange traders for the period July 2008 to April 2013 comprising 34,002 trader-months of observations (one trader-month being the performance of one individual in a single month). Quintiles are defined based on monthly turnover (total traded volume / average account balance). Avg. Balance is the mean daily account balance. Avg. Volume is the mean size of trades done during the month. Avg. Duration is the mean open-to-close holding period of executed trades. Avg. Leverage is the mean value for the volume of each trade divided by the daily account balance on the day the trade was executed. Trades is the number of round-turn trades initiated during a month (trades which overlap months are counted in the month entered). Return is the net return inclusive of spread. Difference to Prior compares the quintile to the next lower one, with p-values provided based on a two-sample T-test. Relative Return adjusts the monthly return by the aggregate average return for the given month. The Q1-Q5 column indicates the return differentials between the least active (Q1) and most active (Q5) quintiles.

Quintile	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	
Turnover	7	40	113	305	1989	
Avg. Balance ($)	30,616	20,457	23,327	10,434	5,348	
Avg. Volume ($)	22,025	30,200	37,341	34,418	44,458	
Avg. Duration (Days)	12.54	3.47	1.74	0.93	0.43	
Avg. Leverage (X:1)	3	8	12	15	27	
Trades	33	35	66	85	182	
Return	-1.00%	-1.34%	-3.12%	-6.27%	-17.62%	**Q1-Q5**
Difference to Prior		-0.34%	-1.78%	-3.15%	-11.35%	-16.62%
p value of T-test		0.27	0.00	0.00	0.00	0.00
Relative Return	4.88%	4.55%	2.76%	-0.39%	-11.74%	

Table 4.6

Descriptive Statistics for Returns for Trader Quintiles Formed on Monthly Trade Frequency and Average Trade Leverage

Sample of 5,357 retail aggregator based foreign exchange traders for the period July 2008 to April 2013 comprising 34,002 trader-months of observations (one trader-month being the performance of one individual in a single month). Quintiles defined based on monthly trades executed for Panel A and month average trade leverage for Panel B. Turnover is total traded volume / average account balance. Avg. Balance is the mean daily account balance. Avg. Volume is the mean size of trades done during the month. Volume is the total value of all trades executed during the month. Avg. Duration is the mean open-to-close holding period of executed trades. Avg. Leverage is the mean value for the volume of each trade divide by the daily account balance on the day the trade was executed. Trades is the number of round-turn trades initiated during a month (trades which overlap months are counted in the month entered). Return is the net return inclusive of spread. Relative return adjusts the monthly return by the aggregate average return for the given month. Difference to Prior compares the quintile to the next lower one, with p-values provided based on a two-sample T-test. The Q1-Q5 column indicates the return differentials between the least active (Q1) and most active (Q5) quintiles.

Panel A: Trade Frequency

Quintile	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	
Trades	2	9	23	56	310	
Turnover	39	134	295	568	1,420	
Avg. Balance ($)	9,030	9,831	11,491	14,912	44,655	
Avg. Volume ($)	30,246	34,367	35,137	33,783	35,034	
Avg. Duration (Days)	9.22	4.29	2.66	1.77	1.10	
Avg. Leverage (X:1)	18.6	15.5	12.9	10.5	6.6	
Return	-3.92%	-4.12%	-5.60%	-6.99%	-8.75%	**Q1-Q5**
Difference to Prior		-0.20%	-1.48%	-1.39%	-1.76%	-4.83%
p value of T-test		0.62	0.00	0.02	0.00	0.00
Relative Return	1.99%	1.71%	0.28%	-1.10%	-2.87%	

Panel B: Average Trade Leverage

Quintile	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	
Avg. Leverage	0.6	2.1	5.2	11.8	44.2	
Turnover	64	185	287	540	1,380	
Avg. Balance ($)	58,748	18,373	7,481	4,307	1,410	
Avg. Volume ($)	18,526	32,410	33,119	40,993	43,382	
Avg. Duration (Days)	9.09	4.26	2.95	1.83	0.98	
Trades	172	91	58	48	34	
Return	-0.38%	-1.94%	-3.37%	-6.70%	-16.96%	**Q1-Q5**
Difference to Prior		-1.56%	-1.43%	-3.33%	-10.26%	-16.58%
p value of T-test		0.00	0.00	0.02	0.00	0.00
Relative Return	5.50%	3.95%	2.51%	-0.82%	-11.08%	

Table 4.7

Deleveraged Returns Across the Trading Activity Quintiles Derived from Turnover, Monthly Trades, and Average Trade Leverage

Sample of 5,357 retail aggregator based foreign exchange traders for the period July 2008 to April 2013 comprising 34,002 trader-months of observations (one trader-month being the performance of one individual in a single month). Panel A indicates monthly hypothetical deleveraged returns – calculated assuming all trades done at size = account balance at time of trade entry - presented in place of realized returns (with returns summed, not compounded). Turnover returns are based on the quintiles formed on monthly turnover rankings from Table 4.5. Trades returns and Average Leverage returns are based on the quintiles formed on monthly rankings from Table 4.6. The Q1-Q5 column indicates the return differentials between the least active (Q1) and most active (Q5) quintiles. The Difference row compares the deleveraged returns to the same quintile realized return, providing an indication of the impact of leverage. Panel B presents mean individual trade deleveraged returns based on the aforementioned quintile rankings.

Panel A: Deleveraged Returns

Quintile	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Q1-Q5**
Turnover	0.82%	-0.50%	0.07%	-1.04%	-2.67%	-3.49%
Difference to Realized Returns	-1.82%	-0.84%	-3.19%	-5.23%	-14.95%	
Trades	-0.21%	-0.34%	-0.20%	-0.53%	-2.03%	-1.82%
Difference to Realized Returns	-3.71%	-3.78%	-5.40%	-6.46%	-6.72%	
Average Leverage	0.31%	-1.18%	-0.74%	-0.95%	-0.77%	-1.07%
Difference to Realized Returns	-0.69%	-0.76%	-2.64%	-5.75%	-16.19%	

Panel B: Per Trade Performance

Quintile	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
Turnover	0.025%	-0.014%	0.001%	-0.012%	-0.015%
Trades	-0.105%	-0.039%	-0.009%	-0.009%	-0.007%
Average Leverage	0.002%	-0.013%	-0.013%	-0.020%	-0.023%

Table 4.8

Experience and its Impact on Trading Activity and Returns

Sample of 5,357 retail aggregator based foreign exchange traders for the period July 2008 to April 2013 comprising 34,002 trader-months of observations (one trader-month being the performance of one individual in a single month). Traders indicated in their profile the years of experience they had trading retail foreign exchange upon joining the social network. Observations indicates the number of trader-months for a given level of trader experience. Monthly trades is the average number of trades executed each month, with Avg. Volume indicating the size, in USD, of those trades. Turnover is total USD volume for the month divided by average account balance. Return is the realized monthly return, while Deleveraged Return indicates cumulative monthly returns of all trades initiated in a given month assuming 1:1 leverage. Avg. Duration indicates the length trades were held. Avg. Leverage indicates the size of trades relative to account size at the time of entry. Avg. Balance is the average of the daily account equity values.

Experience	**0-1**	**1-3**	**3-5**	**5+**	**No Entry**
Observations	6,471	12,218	3,644	7,245	4,424
Monthly Trades	51	76	87	112	79
Avg. Volume ($)	21,209	23,741	35,693	45,862	57,964
Turnover	503	488	484	599	321
Return	-9.02%	-7.11%	-2.78%	-2.50%	-6.00%
Deleveraged Return	-1.29%	-0.43%	-0.60%	-0.57%	-0.62%
Avg. Duration (Days)	3.18	3.87	4.18	4.46	3.25
Avg. Leverage (X:1)	17.25	14.41	10.98	9.49	8.80
Avg. Balance ($)	5,399	9,287	26,587	32,278	30,167

Difference between returns for those with 0-1 or 1-3 years indicated experience and those with 3-5 or 5+ years is significant at the 99% confidence level (t-value 13.93).

Table 4.9

Descriptive Statistics for Returns for Trader Quintiles Formed on Average Monthly Account Balance as a Proxy for Trader Sophistication

Sample of 5,357 retail aggregator based foreign exchange traders for the period July 2008 to April 2013 comprising 34,002 trader-months of observations (one trader-month being the performance of one individual in a single month). Quintiles defined based on monthly average daily account balance. Avg. Leverage is the mean value for the volume of each trade divide by the daily account balance on the day the trade was executed. Avg. Volume is the mean size of trades done during the month. Volume is the total value of all trades executed during the month. Avg. Duration is the mean open-to-close holding period of executed trades. Trades is the number of round-turn trades initiated during a month (trades which overlap months are counted in the month entered). Return is the net return inclusive of spread. Difference to Prior compares the quintile to the next lower one, with p-values provided based on a two-sample T-test. The Q1-Q5 column indicates the return differentials between the least active (Q1) and most active (Q5) quintiles. Deleveraged returns indicates cumulative monthly return of all trades initiated in a given month assuming 1:1 leverage.

Quintile	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	
Avg. Balance ($)	120	587	1,760	4,931	82,386	
Turnover	811	602	425	406	219	
Avg. Volume ($)	2,582	7,240	14,408	29,286	114,601	
Avg. Duration (Days)	279	2.48	3.16	4.48	6.15	
Avg. Leverage (X:1)	30.1	15.0	9.4	6.7	3.0	
Trades	38	53	65	80	166	
Return	-12.85%	-7.48%	-5.01%	-3.28%	-0.83%	**Q1-Q5**
Difference to Prior		5.37%	2.47%	1.73%	2.45%	12.02%
p value of T-Test		0.00	0.00	0.00	0.00	0.00
Deleveraged Return	-0.82%	-0.74%	-1.09%	-0.57%	-0.11%	0.72%

Table 4.10

Correlation of Trader Returns, Leverage, Trades, Experience, Account Balance, and Geographic Region

Sample of 4,046 retail aggregator based foreign exchange traders for the period July 2008 to April 2013 comprising 28,074 trader-months of observations (one trader-month being the performance of one individual in a single month). Leverage is the log of the average trade leverage employed in a given month. Balance is the log of the average daily aggregated account balance for a trader in a given month. Trades is the log of the number of round-turn trades initiated in a given month. Spread is the estimated mean bid/ask spread expressed as a return (always negative). Duration is the logged average holding period, measured in days. Inexperienced is a dummy in which traders indicating 3 years or less of experience are given a value of 1 and all others 0. Region is a dummy in which traders indicating they are United States based are given a value of 1 and all others 0. All random variables exclusive of Spread winsorized at 1% and 99%. P-values provided in parentheses.

	Return	**Avg. Trade Return**	**Leverage**	**Balance**	**Trades**	**Duration**	**Spread**	**Region**	**Inexperienced**
Return	1.00								
Avg. Trade Return	0.27	1.00							
	(0.00)								
Leverage	-0.23	-0.05	1.00						
	(0.00)	*(0.00)*							
Balance	0.18	0.05	-0.58	1.00					
	(0.00)	*(0.00)*	*(0.00)*						
Trades	-0.06	0.08	-0.25	0.28	1.00				
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*					
Duration	0.01	-0.15	-0.24	0.10	-0.20	1.00			
	(0.02)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*				
Spread	-0.01	0.00	0.16	-0.05	0.02	-0.17	1.00		
	(0.40)	*(0.64)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*			
Region	-0.06	-0.02	0.05	-0.10	-0.03	-0.01	-0.01	1.00	
	(0.00)	*(0.01)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.09)*	*(0.23)*		
Inexperienced	-0.09	-0.04	0.14	-0.18	-0.13	-0.02	-0.01	-0.01	1.00
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.01)*	*(0.07)*	*(0.27)*	

Table 4.11

Regression Model Performance for Leverage, Experience, Trade Frequency, Sophistication, Trader Geographic Region, and Trading Style on Trader Monthly Returns, with Month Fixed Effects

$$Return_{i,t} = \alpha + \beta_1 Leverage_{i,t} + \beta_2 Balance_{i,t} + \beta_3 Trades_{i,t} + \beta_4 Region_i + \beta_5 Inexperienced_i + u_{i,t}$$

Sample of 4,046 retail aggregator based foreign exchange traders for the period July 2008 to April 2013 comprising 28,074 trader-months of observations (one trader-month being the performance of one individual in a single month). Leverage is the log of the average trade leverage in a given month. Balance is the log of the average daily aggregated account balance for a trader in a given month. Trades is the log of the number of round-turn trades initiated in a given month. Inexperienced is a dummy in which traders indicating 3 years or less of experience are given a value of 1 and all others 0. Region is a dummy in which traders indicating they are United States based are given a value of 1 and all others 0. Coefficient values are expressed such that, for example, a 1 point increase in the log of average trade leverage results in a 372bp reduction in monthly returns using the value from the in the first test. Results are from an ordinary least squares (OLS) regression clustered on member with robust standard errors (indicated in parenthesis) to account for heteroscedasticity and non-normality. All random variables winsorized at 1% and 99%. Standard errors in parentheses. (* p<0.10; ** p<0.05; *** p<0.01)

Test	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Intercept	0.0252	-0.2141***	-0.0167	-0.0250	-0.0272	-0.0134	0.0304
	(0.0414)	(0.0413)	(0.0425)	(0.0426)	(0.0412)	(0.0417)	(0.0414)
Leverage	-0.0372***					-0.0342***	-0.0342***
	(0.0014)					(0.0018)	(0.0017)
Balance		0.0216***				0.0119***	0.0103***
		(0.0010)				(0.0012)	(0.0012)
Trades			-0.0109***			-0.0235***	-0.0243***
			(0.0015)			(0.0016)	(0.0016)
Region				-0.0289***			-0.0229***
				(0.0052)			(0.0045)
Inexperienced					-0.0429***		-0.0342***
					(0.0052)		(0.0047)
Adjusted R^2	5.79%	3.78%	1.39%	1.23%	1.53%	7.88%	8.38%

Table 4.12
Trading Activity Influence on Monthly and Mean Trade Returns, with Month and Trader Fixed Effects

$$Return_{i,t} = \alpha + \beta_1 Leverage_{i,t} + \beta_2 Balance_{i,t} + \beta_3 Trades_{i,t} + \beta_4 Spread_{i,t} + \beta_5 Duration_{i,t} + u_{tm}$$

Sample of 1,008 retail aggregator based foreign exchange traders for the period July 2008 to April 2013 with at least 10 months of trading activity data comprising 18,238 trader-months of observations (one trader-month being the performance of one individual in a single month). Leverage is the log of the average trade leverage in a given month. Balance is the log of the average daily aggregated account balance for a trader in a given month. Trades is the log of the number of round-turn trades initiated in a given month. Spread is the estimated mean bid/ask spread expressed as a return (always negative). Duration is the logged average holding period, measured in days. Coefficient values are expressed such that, for example, a 1 point increase in the log of average trade leverage results in a 369bp reduction in monthly returns using the value from the in the first test. Results are from an ordinary least squares (OLS) regression clustered on member with robust standard errors. All random variables exclusive of Spread winsorized at 1% and 99%. Standard errors in parentheses. (* p<0.05; ** p<0.01; *** p<0.001)

Test	**Monthly Return**	**Avg. Deleveraged Trade Return**
Intercept	0.0545	-0.00018
	(0.0553)	(0.00175)
Leverage	-0.0369***	-0.00015**
	(0.0030)	(0.00006)
Balance	0.0156***	-0.00003
	(0.0036)	(0.00005)
Trades	-0.0261***	0.00013***
	(0.0021)	(0.00004)
Duration	-0.0026***	-0.00009***
	(0.0003)	(0.00002)
Spread	35.2075	-1.33905
	(33.4803)	(1.56838)
Adjusted R^2	15.20%	9.34%

Table 4.13

Regression Sub-Sample Descriptive Statistics on Account Balances, Trade Frequency, Turnover, Return, Trade Holding Period, and Trade Leverage with Inexperienced and Regional Proportions

Sample of 4,046 retail aggregator based foreign exchange traders for the period July 2008 to April 2013 comprising 28,074 trader-months of observations (one trader-month being the performance of one individual in a single month) including only members with sufficient demographic data to include in the Table 4.11 regressions. All results are based on aggregated values for traders with multiple accounts (where applicable), with monthly returns derived using a weighting based on capital balances for included accounts. Returns are based on the compounded daily returns calculated by the social network platform (when trading activity took place). Daily Capital Balance and Trade Volume values are USD-equivalent based on prevailing exchange rates on the measurement dates. Trades indicates the number of completed round-turn positions, with trades counting in the month they were initiated in the case of positions which overlap months. Turnover is calculated as total volume traded in a month divided by the average daily balance. Trade Duration is the average position holding period (open to close) for round-turn trades initiated in a month, measured in days. Trade Leverage is the average size of the trades initiated in a month relative to the account balance (volume/balance), expressed as a multiple of the account balance. Inexperienced indicates the proportion of observations which are from traders listing 0-3 years experience in their member profile. Region = US indicates the proportion of observations which are from traders listing United States as their geographic home region in their member profile.

	Mean	**25th Percent.**	**Median**	**75th Percent.**	**Standard Deviation**
Daily Capital Balance ($)	15,552	285	1,199	5,156	116,567
Trades	78	6	23	66	321
Turnover (X:1)	522	28	112	392	3,534
Return	-5.96%	-15.71%	-1.79%	3.58%	31.31%
Trade Duration (days)	3.93	0.11	0.45	1.68	22.50
Trade Leverage (X:1)	13.52	1.61	5.21	15.04	23.11
Inexperienced	0.6376				
Region = US	0.4019				

Chapter 5: Social Network Participation Influence on Retail Traders

5.1. Introduction

With the statement "*Investing in speculative assets is a social activity*," Shiller et al. (1984) express the view that market participants actually interact with each other in a meaningful fashion, contrary to the isolationist concept of the investor presented in classic efficient markets theory. Although the authors are not explicitly talking about social networks, they do capture the general idea of groups of investors linked by a set of overlapping interests. Broad research into social networks has a lengthy history,[53] but its specific application in the realm of finance has only relatively recently gained momentum, no doubt motivated in part by the proliferation of online networking platforms.[54]

The challenge for the finance social network research in ascertaining the degree of information transmission and its influence on linked individuals is identifying actual connections. They are often informal, and as such undocumented. This leads to research based on the presumption of network connections rather than on specifically identified ones, meaning the individuals in question are assumed to be socially connected based on commonalities in background, position, or demographics rather than documented interactions (Hochberg et al., 2007, Cohen et al., 2008, Horton and Serafeim, 2009, Cohen et al., 2010, Horton et al., 2012, Pool et al., 2014). As information from online social networks becomes more readily available, researchers are beginning to use observed network connectivity in their analysis, however (Antweiler and Frank, 2004, Mizrach and Weerts, 2009, Simon, 2013, Heimer, 2014b, Simon and Heimer, 2014).

It is important to note that while it may be desirable to have documented direct social connectivity and interaction – and even better, the content of that interaction - the lack thereof does not limit the potential to examine social influence (Horton and Serafeim, 2009). One branch of the financial literature relates to the idea of herding, which is largely based on indirect information transmission as investors make decisions based on what they observe of

[53] See Borgatti et al (2009) for a history and review of social network research.
[54] See Boyd & Ellison (2007) for a general review of the early research into on-line social networks.

market participants who act ahead of them in the markets (Keynes, 1936, Banerjee, 1992, Bikhchandani et al., 1992, Froot et al., 1992, Nofsinger and Sias, 1999, Barber et al., 2009c). There is also a growing related literature on peer effects which seeks to explain financial decision-making in a social context from an observational perspective (Duflo and Saez, 2002, Ng and Wu, 2010, Cooper and Rege, 2011, Kaustia and Knüpfer, 2012, Ahern et al., 2014, Bursztyn et al., 2014, Frydman, 2015). Another research branch seeks to understand the actual transmission of information between and amongst investors with some sort of social connection (Shiller and Pound, 1989, Milton and Raviv, 1993, Antweiler and Frank, 2004, Feng and Seasholes, 2004, Brown et al., 2008). In the context of the financial markets, the development of online social networks provides considerable opportunity to extend the literature. They are platforms for investors to not just receive observational signals which can relate to herding and/or peer effects, but to also receive specific information beyond what others have done in the market. As such, they offer the potential to link the branches of research.

By design, the social research into financial markets participants includes an assumption that the information transmitted through these social networks is of value – meaning it is fundamental in nature and non-public. The main focus of the literature thus far is on the equity markets, so that is perhaps a reasonable expectation. Given the breadth of investment options in the stock market, the ability of any given member to have considerable knowledge of a large portion of even public fundamental information across many companies is virtually nil. Even professional analysts tend to specialize by industry. As such, it is straightforward to envision value accruing to members of a network of equity market investors via the transmission of fundamental information, even if it isn't technically non-public.[55]

What about a smaller, less information-dense market like foreign exchange?[56] In forex - and other small markets - the fundamentals are confined to a much narrower dataset. Macroeconomic information related to a given currency is readily available and there are only a limited number of currencies

[55] This does require accepting the idea that the transmission of new fundamental information is not as efficient as earlier theorized. Hong & Stein (1999) explore this by developing a theory of under-reaction and momentum trading based in part on a relatively slow diffusion of news.
[56] The use of the characterization of "small" here is in regards to the number of available instruments, not the amount of volume transacted.

commonly traded.[57] As such, market participants can much more easily stay up-to-date. This is especially true given the relatively slow general nature of change in key factors such as inflation, trade, capital flows, and interest rates. Further, in the case of a network of retail traders in one of these small markets, it is highly unlikely that truly informed market participants (professionals) would be involved and sharing what they know. As such it can be reasonably concluded that no real new exogenous fundamental information is available to members of a small-market retail trader network.

So where is the value of membership aside from perhaps some non-financial change to ones quality of life (psychic benefit)? One possible alternative form of information which may pass between investors and other financial markets participants is in the form of education. This can either be direct – for example specific information on how to execute a buy order - or indirect learning by observation. These types of alternative transmission can occur regardless of market size and despite the absence of meaningful fundamental information. That said, even if some form of information benefit does accrue to participants in a trader social network, other social aspects may provide offsetting effects such as overconfidence (Han and Yang, 2013). This broadly suggests the presence of useful information in a network - exogenous non-public fundamental information or otherwise - is no guarantee of actual net benefit accruing to members.

Examining the potential existence of non-fundamental and/or non-public information within an investor social network and its impact on members, alongside potential social effects, is the subject of this chapter. The analysis of the activity of traders in a retail forex trader social network offers an opportunity to evaluate member activity and performance in a situation where the non-fundamental information aspects of the transmission process can be highlighted due to the expected lack of exogenous non-public fundamental information.

The remainder of this chapter is structured as follows. Section 5.2 reviews the prior literature and develops the primary hypotheses of the chapter. Section 5.3 provides documentation of the data and methodologies being

[57] While there is a large number of traded currencies, the vast majority of the volume is in a very narrow sub-set of this group. Table 3.4 in Chapter 3 provides a breakdown with respect to the volume distribution for a collection of retail forex traders. Broader volume distribution information may be found in BIS (2014).

employed in the research, with Section 5.4 containing the analysis. Section 5.5 concludes and presents considerations for future research.

5.2. Socially Influenced Trading

5.2.1. Herding behaviour and peer effects

One of the underpinnings of efficient market theory is that the errors of non-rational actors are random. However, if there is a social dynamic to the way traders and investors operate, the potential exists for there to be a non-random aspect to the errors of market participants in their valuation of securities. The behavioural finance research into the limits to arbitrage by Shleifer and Vishny (1997) and those following on address the implications of these non-random errors and the potential for the deviations from fundamental value they create to persist. Herding behaviour, whereby a large number of individuals act in a similar fashion, is at the core of the idea of persistent non-random errors in pricing. This is a process modelled by Cao et al. (2011), and has been used to explain momentum effects in the financial markets.

Keynes (1936) is often given credit for introducing the idea of herding among investors. He does so from the perspective of an iterative process employed by individuals (professional money managers in this case) whereby rather than simply evaluating a security on the basis of its valuation, the actions of other investors are also considered. For example, an investor would buy if they believe other investors will buy, thereby driving price higher.[58] It should be noted, however, that while herding from this perspective is a conscious decision, it need not always be the case. In their review of herding behaviour, Bikhchandani and Sharma (2000) use the terms “intentional herding” and “spurious herding” to differentiate what they identify as two types of behaviour. Intentional herding employs the observation of others (peer effects), while spurious herding is herding motivated by common factors.[59] For the purposes of

[58] This could also be viewed from a momentum trading perspective, which is the basis of the herding observed by Grinblatt et al (1995) and Nofsinger and Sias (1999) with respect to institutional investors.

[59] The authors use the example of a change in interest rates motivating investors to shift asset allocations as an example of this sort of common factors spurious herding.

this thesis, the focus is on the intentional variety, though as the authors admit, distinguishing the two in practice is at best challenging.[60]

Banerjee (1992) investigates the mechanisms of intentional herding and develops a model of investor behaviour which demonstrates how individuals use the decisions of prior movers in their own decision-making. The result is the investor uses their own information less intensely. Bikhchandani et al. (1992) follow a similar course as they propose the informational cascade concept in which investors act on the basis of the actions of those who have gone before them, while Froot et al. (1992) demonstrate that short time horizon speculators not only herd on common information in an effort to learn what other informed traders know, but may incorporate non-fundamental information into that process. Shiller (1995) sees an information cascade effect as well, but is dissatisfied with the first-mover approach taken in the prior research. He instead puts forth differences in group information transmission as a motivating factor in information cascades, which suggests the influence of a social network structure on the herding process.

Regardless of the precise mechanism, however, the potential result of a reliance on others' information by investors, and not their own, is the creation of an inefficient market equilibrium. Instead of contributing to the proper valuation of a security with their "vote" for its worth, investors are essentially allowing others ahead of them to use their vote by proxy. Cipriani and Guarino (2008) show how herding effects can spill over to other markets, leading to persistent disconnects between price and valuation. Conceptually, this information cascade mechanism for herding behaviour is different than the iterative one outlined by Keynes. However, to the extent that both can create self-reinforcing patterns, they arrive at the same destination.

Demonstrating that it is not just investors who herd, Welch (2000) empirically evaluates the investment recommendations of securities analysts, finding that the most recent recommendation has a positive influence on the next two analysts' forecasts and that the consensus overall has a positive influence on analyst recommendation revisions.[61] As the author points out, the motivation for this herding is difficult to ascertain. It could be a case of acting in

[60] See Bikhchandani, et al (1998) for a more general review of herding concepts.
[61] Interestingly, this analyst herding has the potential to create a second level of herding as investors react to the published recommendations.

a fashion which is perceived to be more professionally beneficial rather than trying to be as accurate as possible. Herding on the basis of professional rather than performance considerations is specifically discussed in Scharfstein and Stein (1990) where a model is put forth in which an investment manager uses "…*investment decisions to manipulate the labor market's inferences regarding their ability*…" Such non-performance motivations are also potential explanations for the Hong et al. (2005) findings based on an epidemic thought process that money managers in the same city are inclined to make similar portfolio changes. The same holds true for the Matvos and Ostrovsky (2010) finding that mutual funds are more likely to oppose management when other funds are more likely to do so, all else being equal. Regardless of the motivation, however, the broader idea of individuals using information from those preceding them is valid.

Shive (2010) continues the empirical work in the individual investor arena by employing an epidemic based approach using Finnish data to examine how the holdings of investors influence the behaviour of their investor peers. The analysis indicates the estimated rate of transmission of "rumours" through social contact predicts investor behaviour. Han and Hirshleifer (2015) develop a model whereby active trading strategies are transmitted between members of a social network on a "bragging" basis, which is tested empirically by Simon and Heimer (2014) with findings supportive of just such a transmission occurring.[62] While the propagation of strategies does not relate to herding on the basis of the observation of prior movers, it does speak to herding on the basis of common decision-making factors – spurious herding per the Bikhchandani and Sharma (2000) definition. From the perspective of individual decision-making, this ties in with Bursztyn et al. (2014), who demonstrate the importance of both social learning and social utility in the decision-making of investors when deciding to purchase an asset.

5.2.2. Information transmission

The research into herding behaviour and information cascades often assumes individuals can only gain information from other market participants by observing their behaviour. As Bikhchandani and Sharma (2000) note,

[62] Simon and Heimer (2014) reference a pre-publication working paper version of Han and Hirshleifer (2015) from 2012.

“*Individuals can observe each other’s actions, but not the private information or signals that each player receives.*” Thus, they can see what others are doing, but not why they are doing it. The latter must be inferred in some fashion unless there is also direct communication between individuals. This is the basis of the investor social network concept. Shiller and Pound (1989) find empirically that information is transmitted among investors in a direct fashion in that investors learn of investment opportunities from their peers. Their research, based on survey work, is presented in an epidemic model context in line with some of the herding work mentioned in the previous section, but conceptually it lays the groundwork for research into the broader idea that information is exchanged between and amongst market participants directly rather than just through observation.

One line of research which has recently developed from this idea looks at the link between how social an individual is and their investing behaviour. Hong et al. (2004) find that investors who interact more with their neighbours or attend church are more likely to invest in the financial markets than their relatively less social peers. This is supported by Shanmugham and Ramya (2012) who use a survey-based approach among Indian investors to link social activity to investment activity, finding increased social interaction is related to an increasingly favourable attitude towards trading. Simon (2013) finds a positive relationship between the number of friends an individual has and the frequency of their trading, while Heimer (2014a) finds that social interaction is more apparent among active investors than among passive ones.

Backing out to a more community perspective, a number of examples in the literature use a commonality of geography to draw links between social connectivity (at least presumed) and trading activity. Dorn et al. (2008) examine the correlation of trading done by customers of a German brokerage, finding they place similar trades. Kaustia and Knüpfer (2012), using Finnish data, observe that the returns of local peers influence an investor’s stock market entry decision, especially where the environment is better suited to social learning. Ng and Wu (2010) find that word-of-mouth influences on trading and investing behaviour are strong among investors using a common brokerage branch. This is a follow-up to the broader Feng and Seasholes (2004) use of Chinese data to explore commonality of investing decisions and activity by those geographically linked. They find that investors living near a given company’s headquarters react similarly to information releases. The community idea is also pursued by Brown et al. (2008) who examine how it relates to ownership of stocks among members. They find that the ratio of stock market participation in an investor's local community influences that individual's decision whether to invest. Further, they show that the effects are stronger in communities identified as more social, which is indicated as evidence of word-of-mouth communication. Li (2014) narrows the focus down to the family level in finding that stock market participation increases if an individual's immediate family members become active investors.

Being social and/or being part of a community, however, does not necessarily lead to the transmission of information between market participants, even if the research makes a general assumption along those lines.[63] A path of inquiry using data from chat rooms and discussion forum sites offers an opportunity to observe actual documented interactions between investors. Antweiler and Frank (2004) investigate the influence of stock investing message boards and identify a link to trading volume and returns (to a small degree), and thus find that interactions are predictive of volatility. Banerjee and Kremer (2010) similarly hypothesize that disagreement between market participants over the interpretation of fundamental information leads to greater volume and volatility. This follows on from a similar conceptual model that Milton and Raviv (1993) develop based on variation in the way investors interpret new information which finds that absolute price changes and volume are positively correlated. From a different perspective, Mizrach and Weerts (2009) find profitable returns and a lack of evidence for the disposition effect when looking at the trading activity of a group of chat room traders. These findings provide support for the idea that financial markets participants are influenced by their interactions with each other beyond just simply observing what others are doing, and by extension such interactions can influence prices, which is the argument made by Hirshleifer and Teoh (2009) in making the case that "…*thought and behavior contagion should be incorporated into the theory of capital markets.*"

That said, recent research presents some challenges to the worth of information transmitted through market participant connections and exchanges.

[63] Ahern (2015) actually draws an explicit line of social connectivity and information transmission related to insider trading.

Colla and Mele (2010) find that the value of information linkages do have impacts on market depth and trading profits, but only based on the degree to which they provide positively or negatively correlated signals. Han and Yang (2013) demonstrate that the transmission of exogenous information improves market efficiency, but find that social communication tends to crowd out such information due to "free ride" effects.[64] Further, social communication is indicated as impairing market efficiency when the information transmitted is endogenous in nature. Bakker et al. (2010) also find that social information transmission can impair market efficiency on the basis of a model developed using different trust networks, which are demonstrated to delay price stabilization significantly. This makes intuitive sense, as the requirement of a trust decision before processing new information must necessarily slow the information dissemination process. There is also the communication of confidence, which is addressed by Bloomfield et al. (1996). The authors there find considerable difference between the performance of groups where members can effectively communicate confidence and those where they struggle to do so.

The question which follows from there, however, is what exactly comprises the information being transmitted between investors and traders? The general presumption in much of the research is that the information is of an exogenous fundamental nature related to the valuation of a given security. This is certainly the basis of the work of Colla and Mele (2010) and Han and Yang (2013) just noted. The extent to which such fundamental information is of any value to its recipient is in large part based on the degree to which it is non-public, or at least not yet fully publically disseminated, and that it is exogenous to the network of social connections in question. Significant challenges can be made on both grounds, depending on the nature of the network and the information involved. For example, material non-public information such as that which is shown to be transmitted in the Ahern (2015) examination of the social networks of insider traders and information about pending orders shared

[64] The rise of automated copy trading systems such as those described in Chapter 2 would seem to actually create a process by which free riding can be done automatically. This has interesting implications. If an investor can have an automated process duplicate another's trades – which could actually be said to make the herding process more efficient – then they have no motivation to seek out the information upon which they might free ride. Presumably, that would improve the efficiency of the social information transmission process.

between market professionals – as in the so-called LIBOR scandal[65] and the subsequent exchange rate fixing scandal[66] - is a different prospect than stock tips shared between unsophisticated, non-insider investors.[67]

5.2.3. Social capital

Beyond the actual information content of a network of investors, there is the question of its structure and the impact that may have on how information is transmitted. This is where investor social capital becomes part of the equation with respect to how they are able to acquire and potentially share information. Shiller (1995) indirectly introduces this idea in suggesting that the structure of a social group (network) can influence the way information cascades and the herding effects which may follow.

The concept of social capital is defined "…*broadly as the features of social structure that facilitates action*…" according to Adler and Kwon (2000) in their review. The authors go on to indicate two primary ways the literature has tackled the subject. One is to explore the way an individual is linked to others and how those linkages can influence and facilitate their actions and performance. The other is to evaluate the structure of a network collectively. The two are not mutually exclusive and can potentially overlap. The authors use the example of a firm, which is both a collective network internally and part of other networks externally. Bringing that into a financial context, a bank represents both an internal social network amongst employees as well as having its own "individual" social capital with respect to its linkage to other banks, institutions, and individuals in the global financial network.

Although the literature related to social networks and social capital from a financial perspective is relatively limited to-date, there has been some research focused on the collective network with regards to market structure and prices. Notably, Baker (1984) examines the structure of an options market, finding that the social structures observed affect both the magnitude and direction of option price volatility. Of course much of the herding research mentioned previously can be considered to relate to general market social structure as well. The focus

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[65] Timeline: Libor-fixing scandal - http://www.bbc.co.uk/news/business-18671255
[66] Forex scandal: What is that all about? - http://www.bbc.co.uk/news/business-26526905
[67] O'Connor (2013) points out a number of problems with the sort of information which is shared between and amongst socially connected investors.

of this thesis where social capital is concerned, however, is on the individual member aspect.

Sandefur and Laumann (1998) outline the benefits of a good network position (high social capital), which are "… *information, influence and control, and social solidarity*." From a trader or investor perspective, the tendency may be to think in terms of the first of those three benefits. That is, after all, the basis of what has been discussed in the preceding sections as the big focus of the financial literature related to the relationship between individual market participants. Influence and control is something which certainly can be a factor in networks of certain types of actors, particularly those who would generally be thought of as informed players. While that could also come into play from a social perspective among uninformed market participants, it is not something expected to impact on returns in any sort of direct fashion.

Similarly, social solidarity is not a benefit of social capital which one would expect to contribute in any direct way toward a trader's or investor's performance. It is, however, something which is very much contributory to answering the question "Why do traders join a social network?" Market participation is often a very solitary endeavour for non-professionals. Man being a social animal, there will always be a natural inclination for those who share the common interest of the financial markets in coming together to interact and associate with each other, however. This provides a kind of psychic benefit. The question which will at least start to be addressed in this thesis is whether alongside that benefit there is an offset with respect to performance by any sort of negative aspect of social interaction. Further, social solidarity speaks to the question of trust, and as such has an indirect influence on performance through the process by which a socially connected investor processes information received from another individual or group.

Returning to the question of the sources or forms of social capital, the two primary ones are closure and brokerage (Burt, 2002). Both relate mainly to the first of the benefits listed above – information. Specifically, they are concerned with the dissemination of information through a social network. Closure views a network structure in terms of how interconnected its members are from the perspective of distance. The shorter the distance any piece of information must travel, the faster it will get there and the less degraded that information will be (at least in theory). From this perspective, it is beneficial to be more closely connected with others in the network as it means greater access to information and its faster acquisition. From a trading perspective it is clear how this could be beneficial.[68] The connectivity relationship to returns is the subject of an examination of trading on the Istanbul exchange by Ozsoylev et al. (2011) where more central network members are found to trade earlier and earn greater profits than those on the periphery.

The second form of social capital, brokerage, comes from the idea of structural holes. Structural holes are bridge points where two or more otherwise unconnected groups within a social network are linked. The individual who does that linking is in a position to potentially benefit in two primary ways. One of those benefits is control of information – brokerage. In other words, the one who bridges the groups is in a position to gain advantage from the sharing (or not sharing) of the information present in one group with another where it has not yet reached. The other benefit to filling a structural hole in a network is greater access to a more diverse set of information. This addresses a concern when it comes to the idea of closure, namely redundancy. Someone with a high degree of closure in their network connections may actually receive relatively little in the way of novel information. A network member able to establish a brokerage position, however, can avoid this problem through connection diversity and thus has access to a more useful overall set of information than does others.

Social capital has been much researched in other contexts, but has only started to generate a body of literature in the finance arena. The previously mentioned Horton et al. (2012) and Horton and Serafeim (2009) are two examples of this. The relative newness of investor and trader online social networks along with the limited availability of data related to them means research on the subject in only in its infancy. This thesis represents a step toward expanding that line of exploration.

5.2.4. Social network membership influence on performance

Retail foreign exchange traders are the focus of this thesis. As noted above, forex can be viewed as a small market from the perspective of the breadth of available tradable instruments. As such, it is one where fundamental information is readily available to all participants and is slow-changing. That

[68] It is worth considering that under efficient market theory the assumption is near instant transmission of new information to all market participants, which essentially means everyone has an equally perfect degree of network closure.

being the case, membership in a social network of such individuals would not seem to offer the benefit of availing members of new exogenous non-public fundamental information. The question can therefore be asked what informational benefit, if any, it does offer.

There are potentially other types of information which could reside within the network that may prove of use to members. As noted at the end of Section 3.3 of Chapter 3, there are at least some indications of what individuals perceive as the benefit to joining a social network. Education is one of those motivations, which suggests there are those who join the network looking to gain trading skill by observing and/or interacting with those they perceive to be more experienced, informed, and/or successful than themselves. Banerjee (1992) at least conceptually supports this from the perspective that investors use the behaviour of other investors to provide them with information they do not have. The conclusion there is primarily one of herding effects in terms of investment decisions, but it should be that trading education (reliable or otherwise) can be viewed in a similar fashion, as Han and Hirshleifer (2015) and Simon and Heimer (2014) have done in viewing the propagation of high volatility trading strategies through a network. As Barber et al. (2013) document in the case of speculators in the Taiwan market, some small fraction of traders are persistently profitable, so there likely will exist within any reasonably large trader network a group of members from whom others can at least attempt to seek knowledge, successfully or otherwise.

Given the tendency amongst retail forex traders toward high frequency trading - as suggested by the CitiFX surveys (CitiFX, 2010a, CitiFX, 2010b) and the indication from Chapter 3 that the sample data for this thesis shows more than 75% of trades were held for less than 10 hours according to the distribution of holding periods shown in Table 3.2 - the use of fundamental analysis as a primary motivator is prohibitive. These traders are simply in and out of their trades too quickly and too frequently (on average) for the relatively infrequent changes in fundamental information to be a driver of their decision making. In any case, that is all public information and Evans (2002) finds that public news is rarely the driver of exchange rates in the short term, which is where these traders mainly operate. Since retail traders are not privy to the primary sources of information moving exchange rates in the high frequency time frame (e.g. order flow at the inter-bank level), the focus shifts to the transmission of strategies using available public information. That being the case, one could view the knowledge of anomalous market patterns such as momentum (Gourinchas and Tornell, 2004, Bloomfield et al., 2009b, Baillie and Chang, 2011), carry trade effects (Chaboud and Wright, 2005, Galati et al., 2007, Burnside et al., 2008, Bacchetta and Wincoop, 2010, Baillie and Chang, 2011, Burnside et al., 2011a), and clustering of stop-loss orders (Osler, 2003) as a form of private information endogenous to a social network comprising such traders. Thus, it could be that trading strategies and other educational elements rather than fundamental information are being transmitted. Ellison and Fudenberg (1995) demonstrate the value of word-of-month communication with respect to social learning, even in an environment where contact is not frequent or widespread. Liu et al. (2014) find evidence for effects from both direct (word-of-mouth) and indirect communication (observation) from this perspective.

The ability of new traders to learn of these strategies from experienced network members is predicated on two assumptions. In the case of learning through observation, the requirement is that an inexperienced investor is able to extrapolate a trading strategy by observing transactions. This is not impossible, but it becomes increasingly unlikely as the number of variables involved in the trading strategy increase (assuming the experienced trader even allows such observation of their trading activity in the first place). The alternative learning scenario is an exchange of information through direct interaction. Given the adversarial nature of the retail forex market, as described in Chapter 2 based on the Treynor (1999) definition, the expectation is that there would be a general reluctance among profitable traders to share their “secrets”. Stein (2008) proposes a model in which there is mutual sharing of investment information and ideas,[69] but its first assumption is that the parties are on equal footing. This is hard to argue in a situation where there is a decidedly heterogeneous mixture of experience and sophistication, as in retail forex or other non-professional networks. For that matter, there is a reasonable question as to how interested profitable traders are in even joining the network in the first place. However, profitable investors do join social networks, as documented in at least one case in Section 5.3 below. The degree to which they then interact with others and/or allow themselves to be observed suggests they see an informational benefit of

[69] Gray, et al. (2012) actually find evidence of profitable investment idea sharing among money managers.

their own and/or seek a benefit to network membership beyond information acquisition, as per Sandefur and Laumann (1998).

An alternative source of useful information available to members of the network is the ability to observe the collective sentiment of their peers. The concept of sentiment could be thought of as related to the herding effects discussed earlier. It is a subject which is receiving meaningful and increasing attention - Barberis et al. (1998), Brown and Cliff (2004), Baker and Wurgler (2006), Baker and Wurgler (2007), Tetlock (2007), Stambaugh et al. (2012), and Baker et al. (2012) being noteworthy examples.

As shown in Figure 3.11 of Chapter 3, there were ways the social network members included in this study could track the position imbalances of their fellow retail traders on a collective basis. They could potentially also track the activities of those members with whom they were “friends” - and even others who made their trading activity available to the whole network - in perhaps a less formal fashion.

The question then becomes one of the value of such sentiment data, assuming one is capable of aggregating it in some useable fashion. The literature supports the case for imbalances among investors as indications of sentiment being informative of future price movement in the equity market (Chordia and Subrahmanyam, 2004, Kumar and Lee, 2006, Andrade et al., 2008, Barber et al., 2009b, Kelley and Tetlock, 2012). Klitgaard and Weir (2004) extend that research to analyse positional imbalances in the futures market for currencies and demonstrate how using such information can provide an indication of future price movement, so there is at least some basis to believe observed imbalances in retail forex could also prove informative.

As indicated in Chapter 2, however, the retail segment of the forex market likely has little impact on pricing because it is relatively small in size[70] - especially when so much of its volume is concentrated in the largest currencies[71] - and it is perceived as being uninformed.[72] The implication is therefore that if one were to use the indications of social network member positioning in forex it might be as a contrarian indication rather than in anticipation of a potential positive impact on future exchange rates. Given the

[70] The currency futures market is also small relative to the inter-bank spot market, but includes a number of more informed and sophisticated participants not found in the retail market.
[71] See Tables 3.3 and 3.4 from Chapter 3.
[72] See Section 2.2 of Chapter 2.

high proportion of losing traders in the market,[73] this is perhaps not an irrational position to take.[74] If the positional imbalances of retail forex traders are indeed informative of future exchange rate movement in some fashion, the presumption is that this sort of information would be more likely to be employed successfully by more experienced traders. The issue with this idea is that even if such sentiment information were deemed worth including in the decision-making process, which Elton et al. (1998) contend may not be the case even in markets where retail imbalances are likely more influential on future prices movement – there is a problem with regards to time frame. Such imbalances simply operate at a higher time frame (days, weeks, or months) than active retail forex traders tend to occupy. If one is trading positions lasting hours on average, as is the case in the retail foreign exchange market, imbalances which might be indicative of exchange rate moves over the next month or longer simply are not going to be a major decision-making factor.

Building on these theories, the starting point for the analysis of this chapter is whether there is an informational benefit to be had from network membership. Generally, none would be expected. If there is indeed an educational benefit to be had by the less experienced network members, and no real informational benefit to be had by the more sophisticated members, then only the former group should see any relative gain from network membership, however. Thus, two initial hypotheses may be formulated.

Hypothesis 1: Traders see no general informational benefit from social network membership, therefore membership has no impact on returns.

Hypothesis 2: Unprofitable traders gain a relative benefit over their more profitable peers, therefore their changes in returns after joining the network are relatively better.

These hypotheses are tested in Section 5.4.1.

5.2.5. Network membership influence on trading frequency

In Hong et al. (2004) a model is proposed in which individuals who are more social are more likely to participate in the stock market, all else being equal. This is noted as being motivated by one of two potential drivers (or a

[73] Highlighted by the quarterly account profitability figures from Table 3.7 of Chapter 3.
[74] Though it could be argued that picking the right friends could allow one to follow the winners, so to speak, but that circles things back around to the previously noted potential "free-rider" effects.

combination thereof). One is a learning aspect in which individuals come to understand the potential value of investing, learn how to execute trades, etc. The other is the more social element of talking about investments with friends, which could be seen as related to the attention effect observed by Barber and Odean (2008) with respect to headline grabbing stocks. To the extent that involvement in a social network may increase an individual's enjoyment of the trading process – their entertainment level – this too could motivate a higher level of trading activity as per the Dorn and Sengmueller (2009) findings with respect to German investors.

The research regarding both questions to-date is developing. Ivković and Weisbenner (2007) find a link between the investment activity level of a household and that of their neighbours. The Shive (2010) analysis of investors in Finland finds that social contact in the context of the proportion of investors in a municipality predicts individual trading. Shanmugham and Ramya (2012) find via a survey of Indian investors that one's level of social interaction links positively to their attitude towards trading, while Heimer (2014a) extends on Hong et al. (2004) by linking more social individuals with more active market participants. Mitton et al. (2014) work from a neighbourhood perspective, linking social interaction and investor enthusiasm to increased speculative activity – in this case lottery ticket sales. Broadly speaking, it could be as simple as having friends talking about their trading and the markets keeping the idea of trading at the fore of one's mind.

From a trader network context, whatever social influence motivates an individual to take part in the markets has already happened, removing it from consideration at this stage. That leaves two perspectives which can be taken in viewing the socially motivated trading question with respect to an intentionally joined social network. The first is to consider that merely joining the network indicates an increase in social behaviour. As such, it should have an influence on one's trading activity according to the literature. Since retail forex trading is almost exclusively done online, no consideration needs to be given to any potential change in behaviour engendered by moving to an online environment to take part in an online social network per the findings of Choi et al. (2002). This leads to the third hypothesis of this chapter.

Hypothesis 3: Traders become more active in the markets after joining a social network.

The second perspective with regards to socially motivated trading is just how social is an individual. This steps beyond the simple act of being social as indicated by joining a network and gets into the finer points of whether one develops friends in the network, and if so how many. A further hypothesis can therefore be developed that those with more friends trade more activity.

Hypothesis 4: Increased social connectivity for an individual results in greater frequency of trading.

Section 5.4.2 addresses the relationship between social activity and trading with respect to these hypotheses.

5.2.6. Overconfidence

De Carolis and Saparito (2006) link social network participation, and particularly social capital, with the cognitive biases of overconfidence, illusion of control, and representativeness. The context is the realm of entrepreneurship, but conceptually the application to investing and trading is straightforward. Overconfidence specifically is seen as being driven by three aspects of social network membership. The first is one's position within the network in that better and/or faster access to information can lead one to overestimate their level of knowledge.[75] The second is the trust a member puts in their network contacts. The last is the shared meanings and language which create a bond between network members.

Building on the suggestion of Barber and Odean (2001b) and Barber and Odean (2002) that increased access to information can lead to overconfidence, Park et al. (2013) goes a step further by adding confirmation bias to the mix. They suggest that investors use social interactions to confirm views they already hold rather than seeking out new information (or at least alongside doing so). This leads to overconfidence, which drives what the authors describe as "…*less carefully considered investment decisions.*" Their survey based findings related to a Korean message board system indeed point to just such a bias, which leads to excessive trading and impaired returns. A similar observation is made by Gu et al. (2008) in an analysis of Yahoo! Finance message board activity. Meaningfully, given the context of the discussion of this

[75] While not presented in a social network context, Hirshleifer, et al. (1994) demonstrate how overconfidence can be motivated by investors anticipating earlier access to information.

chapter, there is no specific requirement that the information in question be novel, private, or fundamentally-related.

Two hypotheses can therefore be derived.

Hypothesis 5: Membership in a social network increases trader overconfidence.

Hypothesis 6: Better social network position leads to greater overconfidence in traders.

These hypotheses are tested in Section 5.4.3.

5.2.7. Social network membership and risk seeking/avoidance

The direct interaction of individuals in a social context creates risks beyond that of the type of herding outlined earlier, namely groupthink and group polarization. Whereas herding is generally viewed in the context of information acquisition and usage without necessarily requiring a direct social interaction, groupthink and group polarization are very much to do with social psychology. When examining individual traders and investors, groupthink is not a meaningful consideration as it is focused on consensus building in a group decision-making context.[76] While this could be seen in a case such as an investment committee where a unified decision must be made (buy/sell, portfolio allocation, etc.), it does not readily apply when considering the actions of individual market participants. Group polarization, which addresses changes in individual views when part of a group dynamic, is certainly relevant to investors interacting with each other, though.

Myers and Lamm (1976), in their oft-cited review, state "… *group polarization refers to an increase in the extremity of the average response of the subject population*." What this means is that those inclined toward risky behaviour will tend to be influenced by the group dynamic to make more risky decisions while those inclined toward less risky behaviour will tend to become even more risk averse. Shiller (1987) is among the first to bring the idea of group polarization into the context of investing.

Barber et al. (2003) attempt to explicitly examine the role of group dynamics in comparing decision-making between investment clubs and individuals. They find empirically that a rhetorically based shift toward safer

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[76] See Turner and Pratkanis (1998) for a review of groupthink theory and research.

stocks[77] occurs among the clubs as compared to individual investors. Burton et al. (2006) use laboratory experiments to ascertain the link between group polarization and asset prices, finding those with the most extreme views are much more influential than those with the most conservative, but they do not evaluate whether group involvement moves members toward more extreme behaviours or views, leaving it an open question.

Unfortunately, the data available for the research here includes traders with an excessive level of demographic diversity to be able to evaluate them from the perspective of group polarization. That does not, however, preclude examining other types of social network influence related to risk preference. Research into peer effects points to such a linkage. Cooper and Rege (2011) find in laboratory experiments that observing others taking on risk increases one's likelihood of also doing so. Ahern et al. (2014) find convergence in risk aversion among randomly grouped MBA students. Along a parallel line of thinking, Lu (2011) finds that the performance of peers influences the degree of risk taking by retirement plan investors. In research specifically related to participation in an online social network, Zhu et al. (2012) find on the basis of field and laboratory study that membership increases risk seeking behaviour.

These peer and social effect observations provide the grounds for two further hypotheses to be explored in this chapter.

Hypothesis 7: Membership in a social network results in traders shifting toward more risky trading vehicles.

Hypothesis 8: Traders with better social network position trade more risky instruments.

These hypotheses are tested in Section 5.4.5.

5.3. Data & Methodology

5.3.1. Data and returns

The dataset described in Chapter 3 forms the basis for the analysis which follows, meaning a collection of more than 5,000 members of an on-line retail forex trader social network with varied degrees of trading activity spanning the period of July 2008 to May 2013. As a starting point, the same initial filtering as that described in Section 4.3.1 of Chapter 4 is applied in terms of eliminating

[77] As opposed to an actual move toward lower risk stocks.

the incomplete month of May 2013 and the likely erroneous observations where mean trade leverage in a given month exceeds the 200:1, which is at the high end of broker-permitted leverage use.

Because a main focus in this chapter is on changes in trader performance once they have become part of the network, a sub-set of the data is employed including only those members with activity from both before they joined the network and after doing so. To avoid including periods which feature both member and non-member activity (e.g. a trader joined midway through a month, resulting in part of the month as a member and part as a non-member), the month in which a trader joined the network is excluded. The resulting sub-set is 445 members with 5,610 trader-month observations and 519,512 total completed round-turn transactions.

The analysis performed in this chapter is done at two levels. One is a monthly view with regards to trader returns and trade frequency. The former are the realized values derived in the process described in Section 3.9 of Chapter 3 whereby in the case of a member having multiple trading accounts they are combined on an account balance weighted basis. The latter is simply the sum of all completed round-turn transactions which are initiated in a given month across all available accounts for the trader in question.

The second basis for analysis is at the individual transaction level when evaluating leverage, the bid/ask spread, and excess returns – the latter being the exchange rate move captured by a trade net of the bid/ask spread. The decision to not simply use monthly aggregates across the board (since returns and trade frequency mandate them) is that trade level analysis is more readily generalized with respect to potential impact at the market level, rather than merely at an individual one.

5.3.2. Estimated monthly friend connections

As noted in Chapter 3, the dataset includes only two discreet points of friend link observations – April 2012 and May 2013. It does not include information on when those links were made, nor on when links were broken.[78] As a result, it is impossible to develop an actual time series of friend links, per se. Because the number of friends an individual has in a given month is

[78] The only way to know of the existence of broken friend links is to observe ones which exist in the April 2012 data, but do not in the May 2013 data.

potentially meaningful information in the context of the transmission of data between members in the social network, it is worth at least attempting to estimate monthly friend connections using the data that is available in the dataset. Note that in this context the focus is on all of a member's friend connections, not just connections to others who are among the 445 members subject to this chapter's analysis, as just outlined in Section 5.3.1 above.

A very simple approximation of the number and individual connections each member had in any given month would be the final May 2013 values, or April 2012 for the months up to that point. Friends tend to be accrued over time rather than all at once, however. As such, using the final connections across all months would persistently over-estimate connections, potentially by a very large margin. As such, an alternative estimation solution is desirable.

The estimation problem is here being approached from the perspective the earliest possible point at which two given friends could have connected. This is done by comparing the dates each member joined the network. Since no friend link could have been formed any earlier than the month the later of the two members sharing a link joined the network, that later date is the first possible month for a given friend link. For example, if Member A and Member B are known to be connected and Member A joined in January while Member B joined in July, then July is the earliest possible month for them to have become friends – at least in terms of the social network. Lacking any other basis in the data upon which to operate, the assumption is made that the known friend connections were initiated in this first possible month.

Working from that assumption, a running tally of total friend connections for every member in each month of their membership is derived by summing their estimated new friend connections up to that point:

$$TotalFriends_{i,t} = \sum_{i=1}^{t} MonthFriends_{i,t} \tag{5.1}$$

Where

$TotalFriends_{i,t}$ is the total estimated friend connections for member *i* in month *t*.

$MonthFriends_{i,t}$ is the estimated new friend connections member *i* gained in month *t*.

Thus, in any given month the estimated number of friends for a certain network member is the sum of the total number of the first possible monthly connections for that member over all months they have been in the network to that point. This can be thought of as providing a time series of the maximum number of possible friend connections any given individual could have had in a given month in the dataset. Alternatively, one could think of this methodology as stripping out from each month's set of linkages the friend connections which could not have been in place because one or more of the members were not yet in the network. See Figure 5.1 for a more visual indication of how the estimated friend accumulation process worked.

A short-coming of this methodology is that it essentially assumes a new member instantly connects with all of their friends who were already in the network at the moment of their registration. This concern is somewhat moderated by the fact that the data tested in the analysis to come does not include the month a member actually signed up, as per Section 5.3.1 above. This allows for there to have been a slower friend building process for new members. Unfortunately, this doesn't alter the fact that for existing members the new friend linkages are added instantly. For them, though, the additions are likely to be more gradual and thus to have a smaller impact.

A second short-coming of this methodology is that it has no way of handling "de-friending". Since there is no indication in the dataset of when a given member cut ties with another, there is no way to work that into the friend approximation process. Fortunately, the disconnection of existing friend links is not frequent (at least so far as can be seen in the data). There are 832 instances of members having fewer friends in the May 2013 snapshot than they had in the April 2012 by a total count of 2040 connections. Of those members, nearly 64% reduced their friend links by 10% or less. Only 18% cut those links by 25% or more, with nearly half that number representing members who completely severed all connections (or had connections with them severed). In fact, two members account for 962 of those separated links. Thus, in the broad context, the inability to incorporate de-friending behaviour into the estimation process is likely to be of minor consequence.

The estimation process is begun by working back from the May 2013 data to establish friend connections made between then and April 2012. Validation of the methodology is made in two ways by comparing the estimated

April 2012 connections with the actuals. First, members with no difference in the number of connections between April 2012 and May 2013 are evaluated. This is the bulk of the membership – 4,465 out of 5,901 individuals with friend connections as of the later date. In 98.95% of those cases, the estimates match the actual exactly.

The second test is the case of the 1,498 members where the actual May 2013 friend count differs from the actual April 2012 one.[79] Of course, this group includes individuals who had not actually registered yet as of the earlier date - approximately 350 members in all - leaving 1,143 where estimates could be made. Of that group, the estimated friend links are exactly equal in 23% of cases, meaning that for nearly 84% of members the estimated April 2012 friend links generated by the process outlined above matched the actuals. Of the remainder, there are 140 cases of over-approximation and 737 cases of under-approximation. The mean overestimate is nearly 43%, while the mean underestimate is almost 19%. Those variations seem large, but are heavily influenced by cases with small friend counts. All together, they represent a total variation of 2157 friend links, which is fractionally over 6% of the total number of April 2012 actual connections for the members involved (34,922). There were nearly 41,000 recorded friend links as of April 2012, so the total variation between the estimated value and the actual one is just over 5%.With this confirmation of what would seem to be a reasonable level of accuracy of the methodology, the same process is repeated using the April 2012 actuals to estimate the friend links in the months prior, going back to the beginning of the dataset - or at least to the point where the social network began and the first friend connections were developed.

The intuition is to expect accuracy degradation as one moves further back from one of the actual snapshot points. Having the April 2012 connection data allows for a reset point after working back from May 2013, but from there it is over 3 years back to the first network registrations with no additional correction points available. The rapid growth in membership in 2010 could challenge the accuracy of the estimates in that time frame, but there simply is no way to test. In fact, it isn't even possible to test the idea that estimates

[79] It should be noted this 1,498 number includes 62 members with friend connections in April 2012 who subsequently de-friended all of their friends as of May 2013 resulting in a 0 friend count at that measurement point. Thus, the total number of members with friends at some point in the study period is 5963.

worsen with distance from the start point. That need not be a major hurdle, however. If the monthly estimates derived are viewed as a close approximation of the maximum number of friends a given member could have had at that point then a basis for comparisons over time is established. In any case, these estimates should provide a more realistic friend link approximation than simply assuming the April 2012 or May 2013 friend links were fixed across time – especially for those members with long network histories and/or many friends.

5.3.3. Deriving social capital metrics

In order to perform the analysis of network position documented in Section 5.4.5 below, it is required that certain measures are derived – specifically, those for closure centrality (closeness) and brokerage position (‘dyadic constraint’ or betweenness). Closeness measures the degree to which an individual is connected with other members in terms of distance. The more directly linked one is to others in the network, the more close they are, which is used to gauge one’s information access and speed of acquisition. Betweenness, on the other hand, measures the degree to which a network member connects otherwise unconnected members and/or groups. This presumably provides the opportunity to acquire information which is of greater diversity, and thereby value.

The start point for calculating social capital measures is the estimated member friend connections just outlined above in Section 5.3.2. They are seen as providing a better indication of network position than using one of the fixed reference points (April 2012 or May 2013), especially for the earlier parts of the data set when fewer members are involved. Again, as is noted in Section 5.3.2 above, the network estimation is on the whole of membership, not just on those individuals included in the analysis to come. The values for both closeness and betweenness which are used in the analysis in the next section are those generated using the Pajek software package for each month of the study, the method for which can be found in the appendix to Horton et al. (2012).

It should be noted that the member privacy setting described in Section 3.3 of Chapter 3 is used in developing the social capital metrics. If one member has their privacy option set to not allow anyone to see their trading activity then any friend connections have only a 1-way flow of information from the member with the less restrictive setting to the private one, rather than being a standard

2-way linkage. In the case of two members both having their privacy settings on maximum, no information will actually be transmitted between the two, so no connection actually exists for the purposes of deriving the social capital.[80]

5.3.4. Trade excess return

Although it is not used directly in the analysis which follows, one new measure of trader performance is utilized for classification purposes. That is trade excess return, which is a slight variation on the deleveraged returns used in Chapter 4. It is calculated as the return value of the exchange rate move captured by the trade, exclusive of the bid/ask spread. For example, if a trader entered a long position in USD/JPY at 100 and exited at 110 and there is a bid/ask spread of 0.05, the excess return value for that trade would be 10.05% [(110+0.05) / 100)].[81]

The advantage of using trade excess return rather than a more standard return value is that it removes two potential influencing factors. One is position size, which may be a function of one or more decision processes or factors unrelated to market timing – overconfidence and account balance to name two with previously demonstrated links. The other is instrument selection, which speaks to the cost of the trade. Excess return allows for a narrow focus on just the ability of a trader to pick profitable entry and exit points, regardless of other considerations at play. As such, it is used to identify one of the focus analysis groups, as will be described in the next section.

5.3.5. Defining the groups for analysis

To put the hypotheses developed in Section 5.2 to the test, two groups of network members can be defined. The first comprises those members most likely to be beneficiaries of educational information. For analysis purposes, this group of unsophisticated (unprofitable) traders is defined as those in the bottom quartile of mean monthly returns based on pre-membership observations (-8.91% or worse). Presumably, the poor pre-network performance of these individuals is indicative of some sort of educational lack on their part.

For the second group the reverse is the consideration – namely identifying traders who would not be expected to benefit meaningfully from an

[80] This is an extremely rare circumstance, and even the number of instances of 1-way only connections is relatively small.
[81] The trader would have entered by buying at the offer of 100, and exiting at the bid of 110. The offer at exit would be 110.05, so the market would have moved by 10.05% in full.

educational perspective. These profitable traders comprise the top quartile in terms of mean pre-membership trade excess returns (as described in Section 5.3.4 above). The decision to define this group based on trade level returns rather than monthly returns is made from the perspective that market timing is likely to be the area most directly related to the presence of actionable information in the social network, while other elements which may contribute to aggregated returns (leverage use, trade frequency, etc.) may be influenced by other factors, as hypothesized.

5.4. Analysis

5.4.1. Network influence on member returns

In Section 5.2.4 it is argued that a network of retail traders in a small market environment such as foreign exchange do not benefit from exogenous information passing through the network (Hypothesis 1). Further it is hypothesized that while those unprofitable individuals needing education may gain some benefit from endogenous information in the network, no such benefit would be expected to accrue to already knowledgeable (profitable) traders (Hypothesis 2). That being the case, the former group would be expected to experience a relative performance gain as members while the latter would, excluding other effects, see no real impact from network membership.

Table 5.1 offers a set of top level descriptive statistics. They indicate that in general terms mean monthly returns are significantly lower for in-network observations by approximately 1.80%. Table 5.2 provides support for this finding in the form of a paired means comparison of member vs. non-member monthly returns on a calendar basis which indicates a nearly 3.00% difference. As such, an early indication of not just a general lack of valuable information in the network, but also potentially of some sort of negative – presumably social – effect at work on members.

Addressing the two study groups defined above, Table 5.3 presents a means comparison of pre-membership to post-registration performance for the full 445 trader sample, as well as for those in the bottom quartile based on pre-membership mean monthly returns (the *unprofitable* group), and for those in the top quartile based on pre-membership mean excess trade returns (the *profitable* group). The means in this case are based on winsorized values at the 1% and

99% levels to reduce possible outlier influence. This also serves to moderate any potentially extreme variations for members with limited observations.

The difference in network effects on the unprofitable and profitable study groups is stark. In the case of the unprofitable traders, the indications of an educational benefit are strong. Mean monthly returns are a highly significant 10.90% (1,090 basis points) higher in-network, though still quite poor (-8.74%). For the profitable traders, as hypothesized, there is no sign of an information advantage accruing. The surprising finding is that these top quartile performers are significantly worse off as members of the social network with monthly returns 641 basis points lower per month according to the means comparison.

To confirm these findings with regards to Hypothesis 1 and Hypothesis 2, two models of member return changes can be developed as follows:

$$\begin{aligned} Return_{i,t} = {} & \alpha + \beta_1 Balance_{i,t} + \beta_2 Membership_{i,t} \\ & + \beta_3 Unprofitable_i \\ & + \beta_4 MemberUnprofitable_{i,t} + u_{i,t} \end{aligned} \tag{5.2}$$

$$\begin{aligned} Return_{i,t} = {} & \alpha + \beta_1 Balance_{i,t} + \beta_2 Membership_{i,t} \\ & + \beta_3 Profitable_i + \beta_4 MemberProfitable_{i,t} \\ & + u_{i,t} \end{aligned} \tag{5.3}$$

Where

$Return_{i,t}$ is the return of Trader *i* in month *t*.

$Balance_{i,t}$ is the log of the average daily account balance of Trader *i* in month *t*.

$Membership_{i,t}$ is a dummy for network status of Trader *i* in month *t* (member = 1).

$Unprofitable_i$ is a dummy set to 1 if Trader *i* is among the bottom quartile of traders based on pre-membership mean monthly trade returns.

$Profitable_i$ is a dummy set to 1 if Trader *i* is among the top quartile of traders based on pre-membership mean excess trade returns.

$MemberUnprofitable_{i,t}$ is an interaction term equal to $Membership_{i,t}$ x $Unprofitable_i$.

$MemberProfitable_{i,t}$ is an interaction term equal to $Membership_{i,t}$ x $Profitable_i$.

Through the use of the interaction terms, these models allow for observation of changes in monthly returns with respect to membership for the two study groups relative to the rest of the sample. *Balance* is included as a control on the basis of the findings in Chapter 4 that larger accounts exhibit higher returns, all else being equal. At this point the other potential control variables related to trader activity – leverage use, trade frequency, changing risk preference indicated by variability in the spread of the currency pairs traded, and the duration of trades – are excluded. Any or all of them may be subject to network effects, as will be analysed in sections to come. As such, leaving them out at this stage allows for the observation of the overall effect in the form of changes in monthly returns.

Table 5.4 presents a correlation analysis of the monthly level aggregates and associated dummy variables. As expected, *Membership* and the social capital measures (*Friends*, *Closeness*, *Betweenness*) are positively correlated. Of note, the *Profitable* dummy has a fairly low, though still positive, correlation with *Return*. This would seem to be contradictory, but recall from Section 5.3.5 that the profitable group is defined based on market timing performance rather than monthly returns. The implication of the low correlation is that market timing is actually a relatively minor factor in trader profitability. This could be said to back up the influence of trade frequency and leverage use on returns, at least in terms of a negative sum market, as outlined in Chapter 4. Also noteworthy is the negative correlation between the *Unprofitable* dummy and *Balance*, as well as the positive correlation to *Leverage*, which are both in line with the findings from last chapter.

The above models also incorporate month fixed effects. *Month* is an incremented value starting at 1 for July 2008 observations and finishing at 58 for April 2013. This is used to control for conditions in the market which may impact all traders. Forex trading being two-sided, meaning equal exposure will be long and short, no general market effect might be expected. In the retail forex context, however, that two-sided nature includes market makers and other liquidity providers who are not part of this study where the focus is on individual account holders. In Chapter 2 it is shown that there can be imbalances with respect to individual account holder positions. As such, there is the potential for a broad market impact on trader performance in any given month, thus warranting the inclusion of the month fixed effects in the model.

Table 5.5 presents the results of running an ordinary least squares (OLS) regression with clustering on member to account for correlation of residuals at the individual trader level. Robust standard errors are derived to address heteroscedasticity and non-normality. *Return* and *Balance* are winsorized at 1% and 99% to limit the influence of outlier observations on the results. The Membership column of results is a general test of the influence of membership on returns. The results are highly significant, indicating that being a network member impairs returns by 406bp. This finding cannot be strictly said to indicate a lack of an informational benefit accruing to these profitable traders because it is possible some sort of network effect is overwhelming the information gain. However, to the extent that any information element is present, but not sufficient to counter other effects, the results provide support for at least the spirit of Hypothesis 1 that traders see no general information benefit from social network membership. The question of what is driving that decline in performance is the subject of the sections which follow.

The Unprofitable column adds in the *Unprofitable* dummy, which predictably has a significantly negative coefficient (-0.1112). The third column brings in the *MemberUnprofitable* interaction term. The results indicate that the unprofitable group generally remains unprofitable after joining the network, but the highly significant coefficient for the interaction term (0.1530) indicates that these traders are much more positively influenced by network membership than are others. As such, Hypothesis 2 that unprofitable traders gain a relative benefit over their more profitable peers is supported.

The Profitable column of results from Table 5.5 turns the focus to the profitable group – the more successful market timers who would not be expected to see an educational benefit, and who presumably would be best position to make use of any valuable information which may pass through the network. Here the *Profitable* dummy shows a positive coefficient (0.0424), as is expected. The last column brings in the *MemberProfitable* interaction term, which is significantly negative at -0.0498, further supporting Hypothesis 2.

5.4.2. Does being social increase trading activity?

In Section 5.2.5 it is hypothesized that increase social behaviour would drive increased trading activity. In a negative sum market where the expected return of each trade is negative –at least in terms of the primarily price-taker market participants examined in this study – more trading would on average mean lower returns. As such, an increase in trading activity would help to explain the declining fortunes of the profitable traders observed above.

Table 5.3 provides a means comparison of monthly trades. It shows that generally across all members trade frequency is higher for network members. This holds for the unprofitable, but in the case of the profitable one there is no significant change in trading frequency. The means analysis, however, is potentially subject to an outsized influence from more active traders. There is considerable skew in monthly trade frequency, as can be observed in Table 5.1. That being the case, confirmation must be sought at the trader level. Properly testing the Hypothesis 3 idea that network membership increases activity is accomplished by developing a pair of monthly trade frequency models for unprofitable and profitable members, respectively:

$$\begin{aligned} Trades_{i,t} = \alpha &+ \beta_1 Balance_{i,t} + \beta_2 Leverage_{i,t} + \beta_3 Duration_{i,t} \\ &+ \beta_4 Spread_{i,t} + \beta_5 Membership_{i,t} \\ &+ \beta_6 Unprofitable_i + \beta_7 MemberUnprofitable_{i,t} \\ &+ u_{i,t} \end{aligned} \tag{5.4}$$

$$\begin{aligned} Trades_{i,t} = \alpha &+ \beta_1 Balance_{i,t} + \beta_2 Leverage_{i,t} + \beta_3 Duration_{i,t} \\ &+ \beta_4 Spread_{i,t} + \beta_5 Membership_{i,t} + \beta_6 Profitable_{i,} \\ &+ \beta_7 MemberProfitable_{i,t} + u_{i,t} \end{aligned} \tag{5.5}$$

Where

$Trades_{i,t}$ is the number of round-turn transactions initiated by Trader *i* in month *i*.

$Leverage_{i,t}$ is the log of the average leverage ratio (trade size relative to account balance) for trades entered by Trader *i* in month *i*.

$Duration_{i,t}$ is the log of the average holding period (in days) for trades entered by Trader *i* in month *i*.

$Spread_{i,t}$ is the mean bid/ask spread return value (always negative) for trades done by Trader *i* in month *i*.

Remaining variables as previously defined.

Unlike in the returns case where the decision variables potentially subject to network membership influence are excluded, in this case they are incorporated as controls to allow for the isolation of the network effect on trade frequency. Generally speaking, the expectation is that shorter trade holding periods (*Duration*) are linked to higher trade frequency as a simple function of time. Smaller spreads (less negative spread returns in this case) are also positively related to more frequent trading on the basis that they represent lower transaction costs, allowing for more trades for a given level of expenses. Leverage is the remaining decision variable for a trader aside from market timing. The expectation may be that those who trade relatively larger positions would do so less frequently from the perspective of total market exposure, though opposing arguments could be made on a per trade risk basis.

Here again an OLS regression is employed with member clustering. Month fixed effects are included and all the random variables aside from *Spread* are winsorized at 1% and 99%. *Spread* is excluded as the narrowest spreads are generally to be found among trades in EUR/USD. Therefore, winsorizing at 1% would involve a large portion of the sample. Additionally, the spread return values are based on a very constrained set of values, avoiding the prospect of outlier observations.

The results for these models are found in Table 5.6. The coefficients of all the activity variables are significant and in line with the expectations. The other parts of the results are not consistent with the means analysis, however. *Membership* is not generally indicated as having any impact on trade frequency. In general terms, the unprofitable group is indicated as trading more frequently than the others (0.27), with the reverse true for the profitable segment (-0.49). The profitable group sees no relative effect from network membership. The unprofitable traders, however, are indicated as trading relatively less frequently (-0.39) as network members. This may be an education impact. Adding the interaction term pushes the coefficient for *Unprofitable* up to 0.49, however, on net the unprofitable traders still trade relatively more than others. Regardless, these findings reject the Hypothesis 3 idea that social network membership tends to make traders more active in the market.

Simply being a member of the network seems not to lead to higher trading activity, but there remains the question of the impact of higher levels of network connectivity (more friends) from Hypothesis 4. To examine that question, the models from Equations 5.4 and 5.5 can be modified slightly to incorporate the estimated number of friends an individual has in a given month.

$$
\begin{aligned}
Trades_{i,t} = \alpha &+ \beta_1 Balance_{i,t} + \beta_2 Leverage_{i,t} + \beta_3 Duration_{i,t} \\
&+ \beta_4 Spread_{i,t} + \beta_5 Membership_{i,t} \\
&+ \beta_6 Unprofitable_i + \beta_7 MemberUnprofitable_{i,t} \\
&+ \beta_8 Friends_{i,t} + \beta_7 MemberUnprofitableFriends_{i,t} \\
&+ u_{i,t}
\end{aligned} \tag{5.6}
$$

$$
\begin{aligned}
Trades_{i,t} = \alpha &+ \beta_1 Balance_{i,t} + \beta_2 Leverage_{i,t} + \beta_3 Duration_{i,t} \\
&+ \beta_4 Spread_{i,t} + \beta_5 Membership_{i,t} + \beta_6 Profitable_{i,} \\
&+ \beta_7 MemberProfitable_{i,t} + \beta_8 Friends_{i,t} \\
&+ \beta_7 MemberProfitableFriends_{i,t} + u_{i,t}
\end{aligned} \tag{5.7}
$$

Where

$Friends_{i,t}$ is 1 + the log of the estimated number of friends connects for Trader *i* in month *t*.

$MemberUnprofitableFriends_{i,t}$ is an interaction term equal to $MemberUnprofitable_{i,t}$ x $Friends_{i,t}$.

$MemberProfitableFriends_{i,t}$ is an interaction term equal to $MemberProfitable_{i,t}$ x $Friends_{i,t}$.

Remaining variables as previously defined.

Note the two second level interaction terms incorporating a member's estimated friend count – *MemberUnprofitableFriends* and *MemberProfitableFriends*. They allow for analysis of the relative impact of membership on trade frequency with respect to connectivity level.

Table 5.7 presents the member-clustered OLS regression results based on the above models. The coefficient for the *Friends* variable is positive and significant in all cases, but a caveat must be made. If the regressions are run excluding two members who have far more friends than any others,[82] that significance disappears. In both cases the addition of the *Friends* dummy sees *Membership* shift to negative and significant for all five sets of results, with coefficient values between -0.22 and -0.28 (very slightly less negative when excluding the two high-friend members). That combination of results suggests some small influence in having more friends on how frequently one trades. Overall, however, there is little support for Hypothesis 4 - that being more social in terms of being more connected leads to more frequent trading.

[82] The two members in question have over 1000 and over 500 friends respectively based on the May 2013 observation. By comparison, 99% of members have 119 friends or fewer. The theory is that these two members are network managers who connected with other members as part of their work, not as part of their trading (though both obviously traded to have been included in the sample data).

5.4.3. Does social network membership drive overconfidence?

In Section 5.2.6 it is hypothesized that being part of a social network drives overconfidence from a couple of different perspectives. In Chapter 4 an analysis of leverage use found it to be a better indication of potentially overconfident trading than either account turnover or trade frequency, the two primary measures in the extant literature. It is possible, therefore, to use trade leverage to ascertain whether network involvement drives overconfidence from both the general membership perspective of Hypothesis 5 and the network position perspective of Hypothesis 6. With respect to the findings from Section 5.4.1 above, to the extent that leverage use increases among network members, it would help explain the drop in returns for the profitable group.

The evidence is against an increase in overconfidence for network members, however. Panel B from Table 5.1 indicates lower leverage use by members, which is also reflected in Table 5.2 with respect to both the unprofitable and profitable groups. This can be further analysed for the purposes of testing Hypothesis 5 by adapting the model from Equations 5.2 and 5.3 thus:

$$Leverage_{i,t} = \alpha + \beta_1 Balance_{i,t} + \beta_2 Membership_{i,t} + \beta_3 Unprofitable_{i,t} + \beta_4 MemberUnprofitable_{i,t} + u_{i,t} \quad (5.8)$$

$$Leverage_{t,\mathrm{i}} = \alpha + \beta_1 Balance_{i,t} + \beta_2 Membership_{i,t} + \beta_3 Profitable_{i,t} + \beta_4 MemberProfitable_{i,t} + u_{i,t} \quad (5.9)$$

Note that with the analysis of leverage a shift is made to work at the transaction level rather than in terms of monthly aggregates, as is the case with monthly returns and trade frequency. This is reflected in the change of subscript in the equation to replace Month *m* with Transaction *i*. Thus, the control variables are Trader *t*'s state as of the time of the trade in question being initiated. Otherwise, the variables are as previously defined. The transition to transaction level analysis offers the opportunity for a more generalizable set of results based on a larger number of observations.

Table 5.8 provides correlations for the key study variables at the transaction level comparable to the monthly ones from Table 5.4. As previously noted, and expected, the membership and social capital are all highly correlated. The social capital metrics also show as being positively correlated to

Balance, suggesting that larger traders are more integrated ones. If the expectation is that bigger traders are better ones and that better traders will tend to draw friendship requests, this makes sense. *Excess Return* does not correlate highly with any of the variables involved. Beyond that, the Table 5.8 figures are basically in line with those from Table 5.4.

At the trade level the other activity variables – trade frequency, duration, and spread – must be dropped. This reflects the decision-making factors at this level. Trade frequency is an aggregate which is decided higher up in the process. The *Duration* of any given trade is not generally a decision made by the trader, but rather the result of what happens in the market after the trade is initiated. In the case of *Spread*, it is dropped because currency pair fixed effects are being added alongside the month fixed effects used to this point. Since spread is a function of the currency pair traded, including it as a random variable is redundant.

Table 5.9 provides the member-clustered OLS regression results based on the above models (again with robust standard errors). *Membership* is not significant in any of the tests. Unprofitable traders are indicated as generally using more leverage (0.31), and profitable ones generally use less (-0.32). This is likely to be viewed as expected given the relative levels of presumed sophistication, but none of the coefficient values are strongly significant. In fact, the *Profitable* dummy loses significance entirely when the *MemberProfitable* interaction term is introduced. Not only does this finding offer no evidence in support of Hypothesis 5 with respect to network membership increasing trader overconfidence, in the case of the profitable traders it also does not fit the Kuhnen (2014) proposal that negative outcomes (declining returns) tend to make one more conservative on the basis that the profitable traders experience a drop in returns once in-network (more on this in the next section as well).

The question of whether increased information availability influences greater overconfidence can be addressed by a more granular analysis based on the member's network position. This can be evaluated with respect to Hypothesis 6 in two ways. The first is to bring closeness centrality in to the model to approach the question from the perspective of the volume of available in formation and the prospective speed at which it is received.

$$Leverage_{i,t} = \alpha + \beta_1 Balance_{i,t} + \beta_2 Membership_{i,t} + \beta_3 Unprofitable_{i,t} + \beta_4 MemberUnprofitable_{i,t} + \beta_5 NoFriends_i + \beta_6 Closeness_{i,t} + \beta_7 MemberUnprofitableClose_{i,t} + u_{i,t} \tag{5.10}$$

$$Leverage_{i,t} = \alpha + \beta_1 Balance_{i,t} + \beta_2 Membership_{i,t} + \beta_3 Profitable_{i,t} + \beta_4 MemberProfitable_{i,t} + \beta_5 NoFriends_i + \beta_6 Closeness_{i,t} + \beta_7 MemberProfitableClose_{i,t} + u_{i,t} \tag{5.11}$$

Where

$NoFriends_i$ is a dummy set to 1 if Trader *i* shows no friends as of the May 2013 observation point.

$Closeness_{i,t}$ is the estimated closeness centrality measure for Trader *i* at the time of transaction *t*.

$MemberUnprofitableClose_{i,t}$ is an interaction term equal to $MemberUnprofitable_{i,t}$ x $Closeness_{i,t}$.

$MemberProfitableClose_{i,t}$ is an interaction term equal to $MemberProfitable_{i,t}$ x $Closeness_{i,t}$.

Remaining variables as previously defined.

Recall that closeness is derived from the estimated friend connections of the member in a given month, as described in Section 5.4. The *NoFriends* dummy is incorporated to control for members who never connect with other members of the network. This allows for the interaction terms to only reflect members with the potential to have some degree of centrality. Results for the regressions can be found in Table 5.10. Generally, *Closeness* is not significant with respect to leverage. It does show as just barely significant when including the Profitable dummy variable, but not when excluding the two high-friend members discussed in Section 5.4.2 above. Similarly, the coefficient for the *MemberUnprofitableClose* interaction term is positive and significant in the third column of results, but that falls out when excluding the two members. The MemberUnprofitable interaction term does show as negative and significant regardless, but the significance is weak.

The other way to evaluate the influence of potential information availability effects on leverage use can be accomplished by using the betweenness brokerage social capital measure. Betweenness is less about volume of information and speed of access and more about potential information diversity. Analysis on this basis can be accomplished by replacing *Closeness* in Equations 5.10 and 5.11 with *Betweenness*, the derivation of which is also described in Section 5.4.

$$\begin{aligned} Leverage_{i,t} = \ & \alpha + \beta_1 Balance_{i,t} + \beta_2 Membership_{i,t} \\ & + \beta_3 Unprofitable_{i,t} + \beta_4 MemberUnprofitable_{i,t} \\ & + \beta_5 NoFriends_i + \beta_6 Betweenness_{i,t} \\ & + \beta_7 MemberUnprofitableBetween_{i,t} + u_{i,t} \end{aligned} \tag{5.12}$$

$$\begin{aligned} Leverage_{i,t} = \ & \alpha + \beta_1 Balance_{i,t} + \beta_2 Membership_{i,t} \\ & + \beta_3 Profitable_{i,t} + \beta_4 MemberProfitable_{i,t} \\ & + \beta_5 NoFriends_i + \beta_6 Betweenness_{i,t} \\ & + \beta_7 MemberProfitableBetween_{i,t} + u_{i,t} \end{aligned} \tag{5.13}$$

Where

$Betweenness_{i,t}$ is 1 + the log of the estimated closeness centrality measure for Trader *i* at the time of transaction *t*.

$MemberUnprofitableBetween_{i,t}$ is an interaction term equal to $MemberUnprofitable_{i,t}$ x $Betweenness_{i,t}$.

$MemberProfitableBetween_{i,t}$ is an interaction term equal to $MemberProfitable_{i,t}$ x $Betweenness_{i,t}$.

Remaining variables as previously defined.

Table 5.11 provides the results from running the OLS regressions with member level clustering and robust standard errors. Once again, the *NoFriends* dummy is included to control for members who never connected with other members, thus had no opportunity to develop a brokerage position. The pattern in this case follows that above. When including the two high-friend count members the *Betweeness* coefficient is negative and significant, but when they are excluded no significance is seen. In the case of the betweenness interaction terms, there is no noteworthy result. This means Hypothesis 6 that better social network position leaders to greater overconfidence is not supported.

5.4.4. Does social network membership impact risk aversion?

To a degree the question of the impact of social network membership on risk aversion is addressed in the analysis of leverage above. However, the hypotheses from Section 5.2.7 can be further evaluated by looking at the relative spread levels of the currencies being traded by those in the network.

Doing so will indicate whether network membership tends to see traders shift toward lower or higher risk currency pairs. The means comparison from Table 5.3 shows that trade spread return values are less negative (bid/ask spreads become smaller) for members than non-members, indicating potential increased risk aversion motivated by network membership. With regards to Hypothesis 7, this can be further analysed by modifying the models from Equation 5.8 and 5.9:

$$\begin{aligned} Spread_{i,t} = {} & \alpha + \beta_1 Balance_{i,t} + \beta_2 Leverage_{i,t} + \beta_3 Membership_{i,t} \\ & + \beta_4 Unprofitable_{i,t} + \beta_5 MemberUnprofitable_{i,t} \\ & + u_{i,t} \end{aligned} \tag{5.10}$$

$$\begin{aligned} Spread_{i,t} = {} & \alpha + \beta_1 Balance_{i,t} + \beta_2 Leverage_{i,t} + \beta_3 Membership_{i,t} \\ & + \beta_4 Profitable_{i,t} + \beta_5 MemberProfitable_{i,t} + u_{i,t} \end{aligned} \tag{5.11}$$

Again, the focus is at the transaction level rather than the monthly aggregates. Trade leverage is included in the model as something which the trader can control on a trade-by-trade basis. In this case, the currency pair fixed effects must be dropped due to their redundancy with the dependant variable *Spread*. The results from the member-clustered OLS regressions is presented in Table 5.12. While the means comparison suggests network membership tends to shift traders toward less risky currency pairs (less negative spread values indicating higher liquidity, lower volatility exchange rates), the regressions results do not support that finding. In all cases, the *Membership* dummy fails to come through as significant, so there is no evidence in support of Hypothesis 7 that being more social shifts one toward more risky trading vehicles.

As in the case of leverage, it is worth taking a more granular view from the perspective of closeness and betweenness to see if the presumed informational implications of network connectivity impact on risk aversion may be observed in this context. To test Hypothesis 8, the spread models can be extended to include both measures.

$$\begin{aligned} Spread_{i,t} = {} & \alpha + \beta_1 Balance_{i,t} + \beta_2 Leverage_{i,t} + \beta_3 Membership_{i,t} \\ & + \beta_4 Unprofitable_{i,t} + \beta_5 MemberUnprofitable_{i,t} \\ & + \beta_6 NoFriends_i + \beta_7 Closeness_{i,t} \\ & + \beta_8 MemberUnprofitableClose_{i,t} + u_{i,t} \end{aligned} \tag{5.14}$$

$$\begin{aligned} Spread_{i,t} = {} & \alpha + \beta_1 Balance_{i,t} + \beta_2 Leverage_{i,t} + \beta_3 Membership_{i,t} \\ & + \beta_4 Profitable_{i,t} + \beta_5 MemberProfitable_{i,t} \\ & + \beta_6 NoFriends_i + \beta_7 Closeness_{i,t} \\ & + \beta_8 MemberProfitableClose_{i,t} + u_{i,t} \end{aligned} \tag{5.15}$$

$$
\begin{aligned}
Spread_{i,t} = \alpha &+ \beta_1 Balance_{i,t} + \beta_2 Leverage_{i,t} + \beta_3 Membership_{i,t} \\
&+ \beta_4 Unprofitable_{i,t} + \beta_5 MemberUnprofitable_{i,t} \\
&+ \beta_6 NoFriends_i + \beta_7 Betweenness_{i,t} \\
&+ \beta_8 MemberUnprofitableBetween_{i,t} + u_{i,t}
\end{aligned} \tag{5.16}
$$

$$
\begin{aligned}
Spread_{i,t} = \alpha &+ \beta_1 Balance_{i,t} + \beta_2 Leverage_{i,t} + \beta_3 Membership_{i,t} \\
&+ \beta_4 Profitable_{i,t} + \beta_5 MemberProfitable_{i,t} \\
&+ \beta_6 NoFriends_i + \beta_7 Betweenness_{i,t} \\
&+ \beta_8 MemberProfitableBetween_{i,t} + u_{i,t}
\end{aligned} \tag{5.17}
$$

Tables 5.13 and 5.14 respectively include the results from the closeness and betweenness regressions, following the same methodology as in the prior regressions. In the case of the former, there is a general positive indication for *Closeness* with respect to spread, showing that more central members tend to trade in currency pairs with more narrow spreads. The significance is lower when excluding the two high-friend members discussed in the last two sections, but it is mainly still retained. This is contrary to the hypothesis, however. It is possible that this simply reflects network members connecting with each other on the basis of the currency pairs they trade.

The betweenness regressions provide a stronger set of results. First, the coefficient for the brokerage position metric generally is positive and highly significantly, indicating that members with higher betweenness tend to trade in less risky currency pairs. The *Betweenness* coefficients are lower when excluding the two high-friend members, but they remain positive and significant. Unlike in the case of closeness, this is not a situation where selection of friends on the basis of currency pairs traded could be suggested as being a factor, as that would tend to reduce brokerage position rather than improve it.

Looking at the unprofitable vs. profitable traders, a decidedly split effect is observed, however. The former are indicated as following the just noted pattern, but the latter go in the other direction. Profitable traders with greater brokerage position tend to trade in more volatile currency pairs. The implication is that as a member's brokerage position (betweenness) improves they actually experience lower levels of risk aversion. While this does provide some selective evidence in favour of Hypothesis 8 with respect to greater information access driving more risk-seeking behaviour, it is not overly compelling. As indicated in Panel C of Table 5.1, the 25% to 75% range of observations for *Betweenness* is 0 to 0.00034, making the economic meaningfulness of the Table 5.14 findings dubious. As such, there is more cause to reject Hypothesis 8 than support for it.

5.4.5. Robustness checks

There are a number of decision points with regards to the data preparation and analysis done in this chapter which could be seen as having an influence on the findings. Some are addressed above. Here are others of note.

First, with regards to the friend estimation process outlined in Section 5.3.2, it is possible to add a lag to reflect the fact that people do not instantly connect. For example, rather than a new friend connection being counted in the later of the friends' network registration months, it would only be counted as developing one month later. Two factors rule out continuing on this path. Of primary consideration, introducing any lag automatically cuts out connections which actually did happen during the period skipped over. Perhaps more importantly, the accuracy testing does not provide significantly different results.

Second, no minimum activity filter is applied in generating the results presented in this chapter. Analysis of the monthly aggregates (return and trades) done whereby only traders with at least three months of data pre- and post-registration provides a similar set of results. The values are somewhat different, as would be expected, but they lead to equivalent conclusions. The same is true when applying a minimum 50 trades filter for the transaction based analysis looking at leverage use and spread (currency pair selection).

Third, the month of the study is the time fixed effect variable employed in the regressions throughout this chapter. Using a day or week measure instead produces no difference in the results. The hypothesis to explain this is that there are too many offsetting positions. This means members are on both sides of any broad market effect, thus seeing them cancel out.

Finally, running the analysis developed in this chapter using an alternative panel regression approach per the previous discussion on page 103 (still with robust standard errors) generally produces results with high significance levels. As such, the OLS results are presented as representing the more conservative of the two approaches.

5.5. Conclusions & Further Discussion

The primary focus of this chapter has been to consider the question of individual investors operating in the context of a social structure. In this case it is in the context of an online social network for foreign exchange traders. Social networks are often viewed as sources of useful information to connected members. That information is transmitted amongst members is not in question. The nature of the social network as described in Chapter 3 is such that unless a member has set their privacy preference to not allow anyone to see their activity (a very small minority), then at a minimum all of their friends receive a feed of their activity via their personal dashboard. All members could view the position balance indications for the membership, and additional information was also being passed through the voluntary mechanisms such as private messages and discussion boards, among other media.

While it is acknowledged that information is available in the network and being transmitted across connections, the question is the value of what's being exchanged. The challenge made is that a group of retail (non-professional) traders lacks access to the sort of fundamental non-public information which is of value on a trade-by-trade basis. Thus, members will not receive from each other much, if anything which is actually actionable in their decision-making. The findings of Section 5.4.1 with respect to traders who would seem to be most likely to be able to make use of any such information – those who have demonstrated good market timing ability (profitable traders) - at least make the case that if there is any exogenous fundamental information circulating in the network, it's value is very limited. Being able to examine actual interactions between members would allow for a better analysis on this basis, but the outcomes in the form of returns makes a pretty strong case by themselves.

The alternative form of information discussed in this chapter is education - something endogenous to the network. The dramatic improvement in returns by the most unsophisticated (unprofitable) traders suggests that education is happening. Table 5.5 provides evidence. The basis for it is unclear, however. Is it a simple case of observation, as is a feature of the herding literature? Or is this educational gain a case of direct interaction of traders with each other? Maybe it is some of each.

The question from there is how an individual chooses others to observe and/or with whom to communicate, how they weight what they see and hear, and how they process the incoming information. Each of these factors presumably could play a major part in determining the final value of any information received as a member of a social network. The high frequency nature of the retail forex market means individuals may simply struggle to process the high volume of information coming through in the form of the stream of transactions executed, orders entered, and positions held by their friends, even if those friends are relatively few in number. That makes weighting and/or filtering an extremely important consideration.

Aside from the information question – or perhaps alongside it when considering the educational perspective – is the idea of some type of social impact on member performance. The negative shift in returns for the profitable traders shown in Table 5.5 makes a strong case for just such a factor. Unfortunately, the hypothesized ways network participation may influence members are not borne out by the evidence. In fact, in some places the indications are contrary to the hypotheses, such as in the reduction in trading frequency highlighted in Table 5.6 when social effects are expected to incline investors to trade more often. This might be a function of the profitable traders being sophisticated enough to resist the social/behavioural influences and the unprofitable traders offsetting such effects through the education process.

Admittedly, the limits of the available data in terms of when members connect with each other open up the possibility that an inaccurate representation of the network has been developed. The estimation process outlined in Section 5.3.2 provides a best guess given the available information, but clearly runs the risk of having mistimed connections and cannot account for disconnected relationships. This may be of limited concern for members with higher numbers of friends, particularly when analysing a member's raw friend count, but for less-connected members there could be some significance. And in the case of the social capital measures, there is the risk that missing connections – or ones still in place which should have been dropped – could result in a distorted network map. Tests on a more complete dataset would offer the opportunity to confirm the results presented in Sections 5.4.

Additionally, the lack of specific interaction data and a broader set of demographic information constrains the ability to consider the impact of particularly influential and/or susceptible network members per the findings of Aral and Walker (2012) that certain groups are more influential or susceptible and that members influence each other differently based on considerations such as age, gender, and marital status. Such an exploration would allow for a deeper understanding of the direction of information flow and whether and how influence is projected through the network.

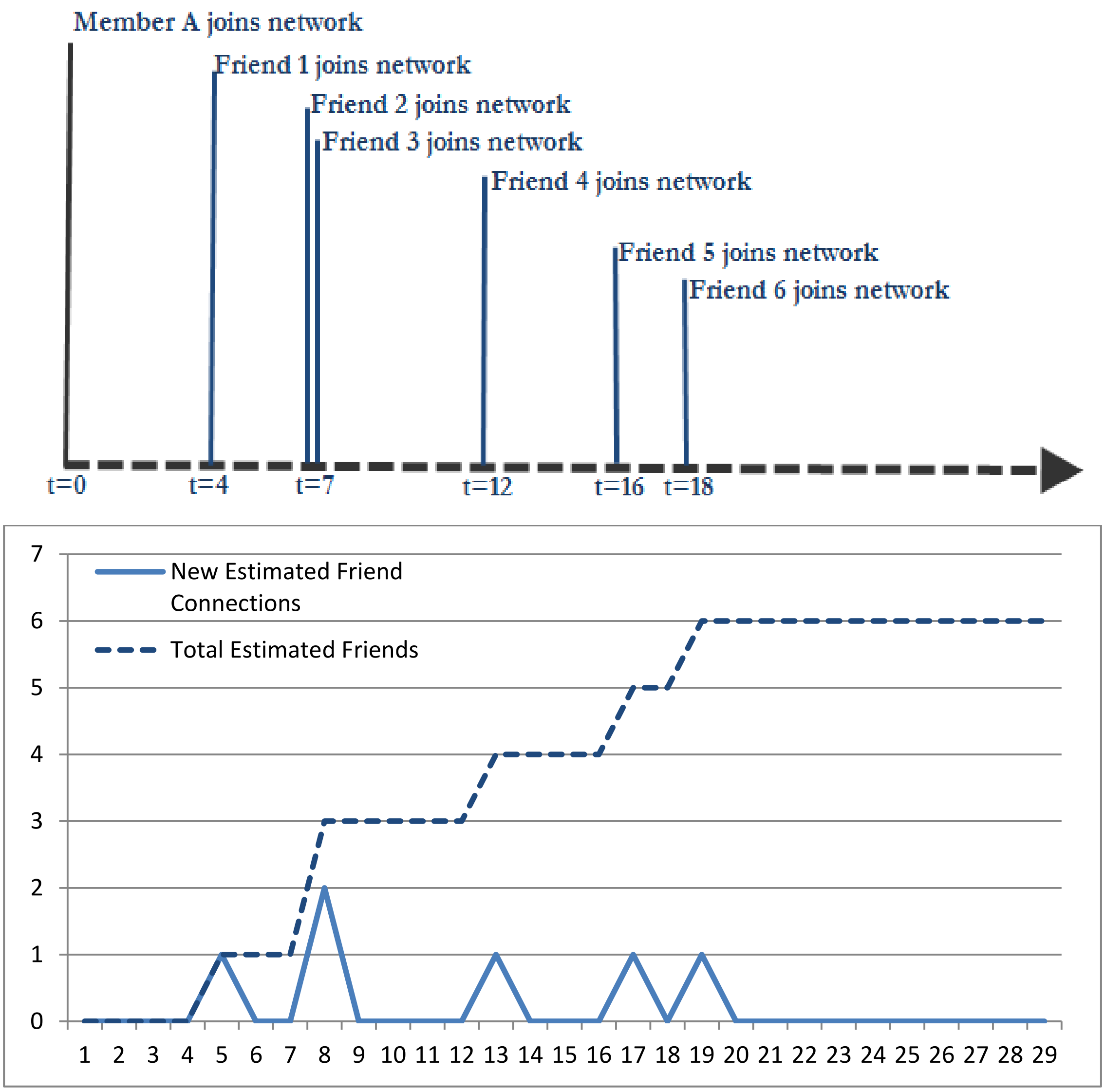
With regards to the behavioural findings (or lack thereof) in relation to trading frequency, overconfidence, and risk aversion it is worth keeping in mind that there is a self-selection aspect to the data. It is possible that simply being willing to become part of the sort of social network in question is an influencing factor in the behavioural aspects of the analysis herein. For example, the willingness to share one's trading activity in real-time suggests a certain inherent level of confidence. This could be a higher level of confidence – perhaps an overconfidence of sorts – than seen in the general trading population. As such, it might preclude seeing a change in behaviour upon joining the network because that variation is already accounted for by the selection process.

Importantly, a final consideration is the actual market timing effectiveness of the traders in question. The lack of another meaningful explanation for the large drop in monthly returns for the more sophisticated (profitable) traders strongly suggests that they have become impaired in the ability to profitably forecast exchange rate movements and manage their entry and exit points. At the same time the unprofitable members improve in this area markedly, which factors heavily in their improved monthly returns. The evidence for this can be found in Table 5.3 which shows how trade excess returns drop significantly for profitable members and rise significant for the unprofitable ones. Analysis of this with respect to the profitable group is the subject of Chapter 6.

Figure 5.1

Friend Estimation

$$TotalFriends_{m,t} = \sum_{i=1}^{t} MonthFriends_{m,i}$$



For each pair of connected members (friends) the earliest possible month in which they could have linked with each other is the later of their respective registration months. Thus, if Member A joined in t=0 and Member B joined in t=4, then t=4 is the earliest possible point at which A and B could have become friends. Lacking a better reference point, this period was considered to be the point at which the friend linked was initiated for the purposes of estimating how many friends each member had in a given month and for deriving social capital measures. In terms of friend count, this then became a summation of all the estimated friend connects of a given member from their initial registration in the network to the current month.

Table 5.1

Descriptive Statistics for Pre-Membership vs. Post-Entry Periods and Social Capital Measures for Social Network Traders

Sample of 445 retail aggregator based foreign exchange traders for July 2008 to April 2013, including 5,610 total trader-month observations (one month of a single trader's performance) and 519,152 round-turn transactions. The month a trader joined the network is excluded. The non-member columns include trader-months and transactions from before joining the network, with the member columns including those from after doing so. Return is the realized monthly return. Balance is the average daily capital level summed for all accounts (where more than one). Trades is the number of round turn positions opened in a month. Leverage is the ratio of trade size to account balance for a trade. Duration is the holding period of a trade measured in days. Spread is the return value of the bid/ask spread of a trade relative to entry price (always negative). Friends is the estimated number of friend connections a member in a given month. Closeness is the centrality social capital metric based on the estimated friend links for that month. Betweenness is the brokerage social capital metric based on the estimated friends links for that month. (* p<0.10; ** p<0.05; *** p<0.01)

Panel A: Monthly Data

	Non-Member: 2474 Observations				**Member: 3136 Observations**				
	Mean	**Std. Dev.**	**25%**	**75%**	**Mean**	**Std. Dev.**	**25%**	**75%**	**Change**
Balance	22,641.57	127,738.30	700.15	8,903.85	44,533.45	234,811.50	934.07	14,853.25	21,891.87***
Trades	81.63	198.09	8	76	101.15	220.19	9	87	19.53***
Return	-1.25%	30.52%	-11.73%	6.99%	-3.04%	27.95%	-9.45%	4.75%	-1.795%**

Panel B: Trades Data

	Non-Member: 201,942 Observations				**Member: 317,210 Observations**				
Leverage	5.29	17.63	0.39	3.95	3.38	12.37	0.14	2.33	-1.91***
Duration	1.57	12.15	0.011	0.366	1.65	11.50	0.020	0.662	0.077**
Spread	-0.0150%	0.0096%	-0.0184%	-0.0077%	-0.0138%	0.0092%	-0.0169%	-0.0076%	0.00119%***

Panel C: Social Capital Measures (215 members, 1577 observations)

	Mean	**Std. Dev.**	**25%**	**75%**
Friends	45.97	177.45	3.00	17.00
Closeness	0.34010	0.05863	0.30435	0.37426
Betweenness	0.00449	0.02401	0.00000	0.00034

Table 5.2
Comparison of Returns of Members in a Trader Social Network with Non-Members on a Month-by-Month Basis

Panel A: Calendar Month Comparison of Means

Sample of 445 retail aggregator based foreign exchange traders for the period July 2008 to April 2013, including 5,610 total trader-month observations (a single trader's performance in one month). Paired mean monthly return comparison of Member vs. Non-Member returns on a calendar month basis. Months with less than 20 traders in each category excluded, leaving 34 total month observations.

Group	Mean	Std. Error	Std. Deviation	95% Conf. Interval	
Members	-0.0317	0.0062	0.0363	-0.0444	-0.0190
Non-Members	-0.0025	0.0064	0.0375	-0.0156	0.0106
Difference	-0.0292	0.0088	0.0515	-0.0472	-0.0112

mean(Difference) = mean(member - non-member) t = -3.3068

Ho: mean(Difference) = 0

Table 5.3

Implications of Membership on Monthly Returns, Trade Frequency, Leverage Use, Currency Pair Selection, and Excess Trade Returns for Individuals in a Retail Forex Traders Social Network

Sample of 445 retail aggregator based foreign exchange traders for the period July 2008 to April 2013, including 5,610 total trader-month observations (a single trader's performance in one month) and 519,152 round-turn transactions. The month a member joined the network is excluded. Monthly Return is aggregated on an account balance weighted basis for members with multiple trading accounts. Monthly Trades is the count of all transaction entered in a given month across all accounts. Trade Leverage is the ratio of transaction volume to mean monthly account balance for a given trade. Trade Spread is the return value of the bid/ask spread (always negative) for a given trade based on the position entry exchange rate. Trade Excess Return is the exchange rate move captured by a given transaction in percent terms relative net of the bid/ask spread with no position size (leverage) factor. Return, trades, and leverage values based on winsorization at 1% and 99%. The indicated significance of the difference between the mean values (Diff) are from an unpaired T-test. (* p<0.10; ** p<0.05; *** p<0.01)

	Base		Unprofitable		Profitable	
Monthly Return	**Count**	**Mean**	**Count**	**Mean**	**Count**	**Mean**
Member	3,136	-3.38%	675	-8.74%	743	-1.01%
Non-Member	2,474	-1.82%	526	-19.64%	432	5.40%
	Diff:	-1.56%***	Diff:	10.90%***	Diff:	-6.41%***
Monthly Trades						
Member	3,136	96.29	675	80.47	743	58.61
Non-Member	2,474	77.08	526	55.43	432	51.57
	Diff:	19.21***	Diff:	25.04***	Diff:	7.04
Trade Leverage						
Member	317,210	3.00	57,411	5.69	44,621	1.99
Non-Member	201,942	4.40	29,300	10.19	22,345	2.16
	Diff:	-1.40***	Diff:	-4.50***	Diff:	-0.16***
Trade Spread						
Member	317,210	-0.0138%	57,411	-0.0140%	44,621	-0.0165%
Non-Member	201,942	-0.0150%	29,300	-0.0155%	22,345	-0.0172%
	Diff:	0.0012%***	Diff:	0.0016%***	Diff:	0.0006%***
Trade Excess Return						
Member	317,210	0.001%	57,411	0.004%	44,621	0.034%
Non-Member	201,942	0.026%	29,300	-0.013%	22,345	0.152%
	Diff:	-0.0252%***	Diff:	0.0171%***	Diff:	-0.119%***

Table 5.4 - Correlations of Study Variables (Monthly Observations)

Sample of 445 retail aggregator based foreign exchange traders for the period July 2008 to April 2013, including 5,610 total trader-month observations (a single trader's performance in one month). Return is the monthly value. Balance is the log of the average daily aggregated account balance for a trader in a given month. Trades is the logged number of completed round-turn transactions begun in the month. Leverage is the log of the average trade leverage employed in a given month. Duration is the log of the mean holding period (in days) of trades done in a given month. Spread is the mean return value of the bid/ask spread of trades done in a given month (always negative). Membership is a dummy set to 1 for in-network observations. Friends is the log of 1 + the estimated number of connections the member had that month. Closeness is the centrality social capital metric based on the estimated number of friends a member has in a given month. Betweenness is the log of 1+ the brokerage social capital metric based on the estimated number of friends a member has in a given month. Profitable is a dummy set to 1 for individuals whose mean excess trade returns pre-membership were in the top quartile. Unprofitable is a dummy set to 1 for individuals whose mean monthly trade returns pre-membership were in the bottom quartile. Return, balance, trades, duration, and leverage values based on winsorization at 1% and 99%. P-values indicated in parentheses.

	Return	**Balance**	**Trades**	**Leverage**	**Duration**	**Spread**	**Friends**	**Closeness**	**Betweenness**	**Membership**	**Profitable**	**Unprofitable**
Return	1.00											
Balance	0.18	1.00										
	(0.00)											
Trades	0.01	0.34	1.00									
	(0.65)	(0.00)										
Leverage	-0.16	-0.64	-0.26	1.00								
	(0.00)	(0.00)	(0.00)									
Duration	-0.01	0.10	-0.23	-0.24	1.00							
	(0.32)	(0.00)	(0.00)	(0.00)								
Spread	0.01	-0.07	0.05	0.19	-0.13	1.00						
	(0.48)	(0.00)	(0.00)	(0.00)	(0.00)							
Friends	-0.03	0.08	0.11	-0.13	-0.02	0.02	1.00					
	(0.01)	(0.00)	(0.00)	(0.00)	(0.20)	(0.07)						
Closeness	-0.04	0.04	0.03	-0.11	-0.01	-0.02	0.89	1.00				
	(0.00)	(0.00)	(0.01)	(0.00)	(0.61)	(0.19)	(0.00)					
Betweenness	0.01	0.14	0.16	-0.15	-0.02	0.07	0.46	0.26	1.00			
	(0.34)	(0.00)	(0.00)	(0.00)	(0.17)	(0.00)	(0.00)	(0.00)				
Membership	-0.03	0.10	0.02	-0.15	-0.06	-0.07	0.46	0.54	0.09	1.00		
	(0.03)	(0.00)	(0.09)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)			
Profitable	0.08	0.08	-0.11	-0.16	0.10	-0.14	-0.05	-0.01	-0.05	0.08	1.00	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.31)	(0.00)	(0.00)		
Unprofitable	-0.22	-0.29	-0.06	0.23	0.01	0.01	-0.06	-0.04	-0.04	0.00	-0.14	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.40)	(0.47)	(0.00)	(0.00)	(0.00)	(0.81)	(0.00)	

Table 5.5

Implications of Membership on Monthly Returns for Individuals in a Retail Forex Traders Social Network, with Month Fixed Effects

$$\boldsymbol{Return_{i,t} = \alpha + \beta_1 Balance_{i,t} + \beta_2 Membership_{i,t} + \beta_3 Unprofitable_i + \beta_4 MemberUnprofitable_{i,t} + u_{i,t}}$$

Sample of 445 retail aggregator based foreign exchange traders for the period July 2008 to April 2013, including 5,610 total trader-month observations (a single trader's performance in one month). The month a member joined the network is excluded. Balance is the log of the mean daily account balance across all active member accounts, winsorized at the 1% and 99% levels. Membership is a dummy set to 1 for months in which an individual is part of the network. Unprofitable is a dummy set to 1 for individuals whose mean monthly trade returns pre-membership were in the bottom quartile. Profitable is a dummy set to 1 for individuals whose mean excess trade returns pre-membership were in the top quartile. Member-Unprofitable and Member-Unprofitable are interaction terms equal to Membership x Unprofitable and Profitable respectively. Results are from an Ordinary Least Squares (OLS) regression clustered on member with robust standard errors using month fixed effects, and are expressed in terms of monthly return, which is aggregated on an account balance weighted basis for members with multiple trading accounts. Standard errors indicated in parenthesis below the coefficient values. (* p<0.10; ** p<0.05; *** p<0.01)

Test	Membership	Unprofitable	Member-Unprofitable	Profitable	Member-Profitable
Intercept	-0.1961***	-0.1099*	-0.0765	-0.1942***	-0.1962***
	(0.0566)	(0.0584)	(0.0611)	(0.0565)	(0.0564)
Balance	0.0218***	0.0157***	0.0151***	0.0212***	0.0212***
	(0.0025)	(0.0024)	(0.0023)	(0.0025)	(0.0025)
Membership	-0.0406***	-0.0322***	-0.0644***	-0.0418***	-0.0314***
	(0.0103)	(0.0094)	(0.0088)	(0.0101)	(0.0114)
Unprofitable		-0.1112***	-0.1979***		
		(0.0150)	(0.0188)		
Member-Unprof			0.1530***		
			(0.0248)		
Profitable				0.0424***	0.0731***
				(0.0101)	(0.0166)
Member-Prof					-0.0498**
					(0.0206)
Adjusted R^2	3.65%	6.42%	7.84%	4.07%	4.20%

Table 5.6

Implications of Membership on Trade Frequency for Individuals in a Retail Forex Trader Social Network, with Month Fixed Effects

$$\boldsymbol{Trades_{i,t} = \alpha + \beta_1 Balance_{i,t} + \beta_2 Leverage_{i,t} + \beta_3 Duration_{i,t} + \beta_4 Spread_{i,t} + \beta_5 Membership_{i,t} + \beta_6 Unprofitable_i + \beta_7 MemberUnprofitable_{i,t} + u_{i,t}}$$

Sample of 445 retail aggregator based foreign exchange traders for the period July 2008 to April 2013, including 5,610 total trader-month observations (a single trader's performance in one month). The month a member joined the network is excluded. Balance is the log of the mean daily account balance across all active member accounts. Leverage is the log of the mean trade leverage for all transactions entered in the month. Duration is the log of the mean holding period (in days) for all transactions entered in the month. Spread is the mean bid/ask spread return value (always negative) of all trades entered in the month. Balance, Leverage, and Duration are all winsorized at 1% and 99% Membership is a dummy set to 1 for months in which an individual is part of the network. Unprofitable is a dummy set to 1 for individuals whose mean monthly trade returns pre-membership were in the bottom quartile. Profitable is a dummy set to 1 for individuals whose mean excess trade returns pre-membership were in the top quartile. Member-Unprofitable and Member-Unprofitable are interaction terms equal to Membership x Unprofitable and Profitable respectively. Results are from an Ordinary Least Squares (OLS) regression clustered on member with robust standard errors using month fixed effects, and are expressed in terms of the log of the number of trades entered in the month. Standard errors indicated in parenthesis below the coefficient values. (* p<0.10; ** p<0.05; *** p<0.01)

Test	**Membership**	**Unprofitable**	**Member-Unprofitable**	**Profitable**	**Member-Profitable**
Intercept	1.53***	1.36**	1.30**	1.56***	1.55***
	(0.57)	(0.59)	(0.59)	(0.57)	(0.57)
Balance	0.20***	0.22***	0.22***	0.20***	0.20***
	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
Leverage	-0.20***	-0.21***	-0.21***	-0.21***	-0.21***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Duration	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Spread	1296.49**	1320.77**	1341.57**	1033.94**	1035.57**
	(549.53)	(541.14)	(539.71)	(527.16)	(528.02)
Membership	-0.13	-0.15	-0.07	-0.12	-0.11
	(0.10)	(0.10)	(0.11)	(0.10)	(0.12)
Unprofitable		0.27*	0.49***		
		(0.15)	(0.15)		
Member-Unprof			-0.39*		
			(0.22)		
Profitable				-0.49***	-0.47***
				(0.12)	(0.15)
Member-Prof					-0.04
					(0.19)
Adjusted R^2	21.29%	21.68%	21.89%	22.67%	22.66%

Table 5.7

Implications of Friend Connections on Trade Frequency for Members of a Retail Forex Trader Social Network, with Month Fixed Effects

$$\begin{aligned} \boldsymbol{Trades_{i,t}} = \alpha &+ \boldsymbol{\beta_1 Balance_{i,t}} + \boldsymbol{\beta_2 Leverage_{i,t}} + \boldsymbol{\beta_3 Duration_{i,t}} \\ &+ \boldsymbol{\beta_4 Spread_{i,t}} + \boldsymbol{\beta_5 Membership_{i,t}} + \boldsymbol{\beta_6 Unprofitable_{i}} \\ &+ \boldsymbol{\beta_7 MemberUnprofitable_{i,t}} + \boldsymbol{\beta_8 Friends_{i,t}} \\ &+ \boldsymbol{\beta_7 MemberUnprofitableFriends_{i,t}} + \boldsymbol{u_{i,t}} \end{aligned}$$

Sample of 445 retail aggregator based foreign exchange traders for the period July 2008 to April 2013, including 5,610 total trader-month observations (a single trader's performance in one month). The month a member joined the network is excluded. Balance is the log of the mean daily account balance across all active member accounts. Leverage is the log of the mean trade leverage for all transactions entered in the month. Duration is the log of the mean holding period (in days) for all transactions entered in the month. Spread is the mean bid/ask spread return value (always negative) of all trades entered in the month. Membership is a dummy set to 1 for months in which an individual is part of the network. Unprofitable is a dummy set to 1 for individuals whose mean monthly trade returns pre-membership were in the bottom quartile. Profitable is a dummy set to 1 for individuals whose mean excess trade returns pre-membership were in the top quartile. Member-Unprofitable and Member-Unprofitable are interaction terms equal to Membership x Unprofitable and Profitable respectively. Friends is the log of 1 plus the estimated number of friend connections for the trader in that month. Balance, Leverage, Duration, and Friends are all winsorized at 1% and 99%. Member-Unprofitable-Friends and Member-Profitable-Friends are interactions terms which are calculated as the prior interaction terms x Friends. Results are from an Ordinary Least Squares (OLS) regression clustered on member with robust standard errors using month fixed effects, and are expressed in terms of the log of the number of trades entered in the month, winsorized at 1% and 99%. Standard errors indicated in parenthesis below the coefficients. (* p<0.10; ** p<0.05; *** p<0.01)

Test	**Friends**	**Unprofitable**	**Unprofitable-Friends**	**Profitable**	**Profitable-Friends**
Intercept	1.49***	1.26**	1.26**	1.52***	1.55***
	(0.57)	(0.59)	(0.58)	(0.57)	(0.57)
Balance	0.21***	0.22***	0.22***	0.20***	0.20***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Leverage	-0.19***	-0.20***	-0.20***	-0.21***	-0.21***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Duration	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Spread	1157.73**	1200.64**	1200.45**	927.41*	937.74*
	(516.53)	(505.60)	(505.98)	(507.17)	(508.04)
Membership	-0.27***	-0.23**	-0.22**	-0.25**	-0.28**
	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)
Unprofitable		0.48***	0.48***		
		(0.15)	(0.15)		
Member-Unprof		-0.34	-0.35*		
		(0.21)	(0.21)		
Friends	0.12**	0.12**	0.12**	0.11*	0.13**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Mem-Unprof-			0.01		
			(0.19)		
Member-Prof				0.00	0.16
				(0.18)	(0.21)
Mem-Prof-Friends					-0.17
					(0.11)
Adjusted R^2	21.95%	22.57%	22.55%	23.16%	23.30%

Table 5.8 - Correlations of Study Variables (Trades)

Sample of 445 retail aggregator based foreign exchange traders for the period July 2008 to April 2013, including 519,152 round-turn transactions. Excess Return is the trade return in exchange rate terms (no position size factor) net of the bid/ask spread. Balance is the log of the average daily aggregated account balance for the trader in the month of the observed trade. Leverage the logged value of the ratio of trade size to account balance. Duration is the log of the trade holding period (in days). Spread is the return value of the bid/ask spread (always negative). Membership is a dummy set to 1 for in-network observations. Friends is the log of 1 + the estimated number of connections the member had that month. Closeness is the centrality social capital metric based on the estimated number of friends a member has in a given month. Betweenness is the log of 1+ the brokerage social capital metric based on the estimated number of friends a member has in a given month. Profitable is a dummy set to 1 for individuals whose mean excess trade returns pre-membership were in the top quartile. Unprofitable is a dummy set to 1 for individuals whose mean monthly trade returns pre-membership were in the bottom quartile. Excess return, balance, duration, and leverage values based on winsorization at 1% and 99%. P-values indicated in parentheses.

	Excess Return	Balance	Leverage	Duration	Spread	Friends	Closeness	Betweenness	Membership	Profitable	Unprofitable
Excess Return	1.00										
Balance	0.01	1.00									
	(0.00)										
Leverage	0.02	-0.61	1.00								
	(0.00)	(0.00)									
Duration	-0.07	0.08	-0.22	1.00							
	(0.00)	(0.00)	(0.00)								
Spread	-0.04	-0.03	0.04	-0.15	1.00						
	(0.00)	(0.00)	(0.00)	(0.00)							
Friends	0.00	0.25	-0.19	0.07	0.14	1.00					
	(0.46)	(0.00)	(0.00)	(0.00)	(0.00)						
Closeness	-0.02	0.18	-0.15	0.07	0.14	0.90	1.00				
	(0.00)	(0.00)	(0.00)	(0.00)	(0.20)	(0.07)					
Betweenness	0.01	0.25	-0.22	0.16	0.14	0.69	0.53	1.00			
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)				
Membership	-0.03	0.20	-0.17	0.10	0.06	0.45	0.55	0.19	1.00		
	(0.00)	(0.00)	(0.00)	(0.00)	(0.17)	(0.00)	(0.00)	(0.00)			
Profitable	0.05	0.08	-0.12	0.18	-0.10	-0.14	-0.12	-0.09	0.04	1.00	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		
Unprofitable	-0.01	-0.33	0.26	0.03	-0.01	-0.12	-0.11	-0.10	0.05	-0.08	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

Table 5.9

Membership Impact on Leverage Use for Individuals in a Retail Forex Trader Social Network, with Month and Currency Pair Fixed Effects

$$\boldsymbol{Leverage_{i,t} = \alpha + \beta_1 Balance_{i,t} + \beta_2 Membership_{i,t} + \beta_3 Unprofitable_{i,t} + \beta_4 MemberUnprofitable_{i,t} + u_{i,t}}$$

Sample of 445 retail aggregator based foreign exchange traders for the period July 2008 to April 2013, including 519,152 round-turn transactions. The month a member joined the network is excluded. Balance is the log of the mean daily account balance across all active member accounts, winsorized at the 1% and 99% levels. Membership is a dummy set to 1 for months in which an individual is part of the network. Unprofitable is a dummy set to 1 for individuals whose mean monthly trade returns pre-membership were in the bottom quartile. Profitable is a dummy set to 1 for individuals whose mean excess trade returns pre-membership were in the top quartile. Member-Unprofitable and Member-Unprofitable are interaction terms equal to Membership x Unprofitable and Profitable respectively. Results are from an Ordinary Least Squares (OLS) regression clustered on member with robust standard errors using month and currency pair fixed effects, and are expressed in terms of the log of trade leverage, which is expressed as a multiple of account balance and winsorized at 1% and 99%. Standard errors indicated in parenthesis below the coefficient values.
(* p<0.10; ** p<0.05; *** p<0.01)

Test	Membership	Unprofitable	Member-Unprofitable	Profitable	Member-Profitable
Intercept	5.26***	5.04***	5.02***	5.24***	5.24***
	(0.57)	(0.59)	(0.60)	(0.57)	(0.57)
Balance	-0.55***	-0.53***	-0.53***	-0.54***	-0.54***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Membership	0.01	-0.03	0.01	0.01	0.00
	(0.22)	(0.20)	(0.23)	(0.22)	(0.24)
Unprofitable		0.31*	0.47*		
		(0.17)	(0.27)		
Member-Unprof			-0.25		
			(0.26)		
Profitable				-0.32*	-0.35
				(0.18)	(0.31)
Member-Prof					0.05
					(0.29)
Adjusted R^2	43.58%	43.87%	43.92%	43.87%	43.87%

Table 5.10
Implications of Centrality on Leverage Use for Members of a Retail Forex Trader Social Network, with Month and Currency Pair Fixed Effects

$$\begin{aligned} \boldsymbol{Leverage_{i,t}} = \boldsymbol{\alpha} + \boldsymbol{\beta_1 Balance_{i,t}} + \boldsymbol{\beta_2 Membership_{i,t}} + \boldsymbol{\beta_3 Unprofitable_{i,t}} \\ + \boldsymbol{\beta_4 MemberUnprofitable_{i,t}} + \boldsymbol{\beta_5 NoFriends_i} \\ + \boldsymbol{\beta_6 Closeness_{i,t}} + \boldsymbol{\beta_7 MemberUnprofitableClose_{i,t}} + \boldsymbol{u_{i,t}} \end{aligned}$$

Sample of 445 retail aggregator based foreign exchange traders for the period July 2008 to April 2013, including 519,152 round-turn transactions. Balance is the log of the mean daily account balance across all active member accounts, winsorized at 1% and 99% Membership is a dummy set to 1 for months in which an individual is part of the network. Unprofitable is a dummy set to 1 for individuals whose mean monthly trade returns pre-membership were in the bottom quartile. Profitable is a dummy set to 1 for individuals whose mean excess trade returns pre-membership were in the top quartile. Member-Unprofitable and Member-Unprofitable are interaction terms equal to Membership x Unprofitable and Profitable respectively. Closeness is the centrality social capital measure based on the estimated friend connections for the trader in that month. Member-Unprofitable-Close and Member-Profitable-Close are interactions terms which are calculated as the prior interaction terms x Closeness. Results are from an Ordinary Least Squares (OLS) regression clustered on member with robust standard errors using month and currency pair fixed effects, and are expressed in terms of the log of trade leverage, winsorized at 1% and 99%. Standard errors indicated in parenthesis below the coefficients. (* p<0.10; ** p<0.05; *** p<0.01)

Test	Close	Unprofitable	Unprofitable-Closeness	Profitable	Profitable-Closeness
Intercept	5.21***	5.00***	4.99***	5.19***	5.16***
	(0.55)	(0.57)	(0.57)	(0.54)	(0.54)
Balance	-0.54***	-0.52***	-0.52***	-0.54***	-0.53***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Membership	0.11	0.12	0.17	0.14	0.17
	(0.21)	(0.23)	(0.24)	(0.23)	(0.23)
No Friends	-0.02	-0.01	-0.03	-0.05	-0.04
	(0.22)	(0.21)	(0.21)	(0.21)	(0.21)
Closeness	-0.56	-0.51	-0.78	-0.72*	-0.84*
	(0.44)	(0.43)	(0.48)	(0.42)	(0.44)
Unprofitable		0.47*	0.47*		
		(0.27)	(0.27)		
Member-Unprof		-0.30	-0.53*		
		(0.27)	(0.30)		
Mem-Unprof-Close			1.64**		
			(0.75)		
Profitable				-0.37	-0.37
				(0.28)	(0.28)
Member-Prof				-0.01	-0.15
				(0.25)	(0.26)
Mem-Prof-Close					1.17
					(0.90)
Adjusted R^2	43.75%	44.06%	44.27%	44.14%	44.21%

Table 5.11
Brokerage Position Impact on Leverage for Individuals in a Retail Forex Trader Social Network, with Month and Currency Pair Fixed Effects

$$\begin{aligned} \boldsymbol{Leverage_{i,t}} = \boldsymbol{\alpha} + \boldsymbol{\beta_1 Balance_{i,t}} + \boldsymbol{\beta_2 Membership_{i,t}} + \boldsymbol{\beta_3 Unprofitable_{i,t}} \\ + \boldsymbol{\beta_4 MemberUnprofitable_{i,t}} + \boldsymbol{\beta_5 NoFriends_i} \\ + \boldsymbol{\beta_6 Betweenness_{i,t}} + \boldsymbol{\beta_7 MemberUnprofitableBetween_{i,t}} \\ + \boldsymbol{u_{i,t}} \end{aligned}$$

Sample of 445 retail aggregator based foreign exchange traders for the period July 2008 to April 2013, including 519,152 round-turn transactions. Balance is the log of the mean daily account balance across all active member accounts, winsorized at 1% and 99% Membership is a dummy set to 1 for months in which an individual is part of the network. Unprofitable is a dummy set to 1 for individuals whose mean monthly trade returns pre-membership were in the bottom quartile. Profitable is a dummy set to 1 for individuals whose mean excess trade returns pre-membership were in the top quartile. Member-Unprofitable and Member-Unprofitable are interaction terms equal to Membership x Unprofitable and Profitable respectively. Betweenness is the log of 1 plus the brokerage social capital measure based on the estimated friend connections for the trader in that month. Member-Unprofitable-Between and Member-Profitable-Between are interactions terms which are calculated as the prior interaction terms x Betweenness. Results are from an Ordinary Least Squares (OLS) regression clustered on member with robust standard errors using month and currency pair fixed effects, and are expressed in terms of the log of trade leverage, winsorized at 1% and 99%. Standard errors indicated below the coefficients.
(* p<0.10; ** p<0.05; *** p<0.01)

Test	**Between**	**Unprofitable**	**Unprofitable-Betweenness**	**Profitable**	**Profitable-Betweenness**
Intercept	5.04***	4.82***	4.82***	5.01***	5.01***
	(0.55)	(0.57)	(0.57)	(0.54)	(0.54)
Balance	-0.52***	-0.51***	-0.51***	-0.52***	-0.52***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Membership	0.06	0.08	0.08	0.06	0.06
	(0.19)	(0.21)	(0.22)	(0.20)	(0.20)
No Friends	-0.02	-0.02	-0.01	-0.03	-0.03
	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)
Betweenness	-5.81***	-5.84***	-5.85***	-6.25***	-6.25***
	(1.34)	(1.38)	(1.38)	(1.40)	(1.40)
Unprofitable		0.50*	0.50*		
		(0.27)	(0.27)		
Member-Unprof		-0.34	-0.36		
		(0.27)	(0.26)		
Mem-Unprof-Betw			30.96		
			(38.70)		
Profitable				-0.37	-0.37
				(0.29)	(0.29)
Member-Profitable				-0.01	-0.02
				(0.26)	(0.26)
Mem-Prof-Betw					55.36
					(45.14)
Adjusted R^2	44.32%	44.66%	44.67%	44.72%	44.72%

Table 5.12

Implications of Membership on Currency Pair Selection for Members of a Retail Forex Trader Social Network, with Month Fixed Effects

$$\boldsymbol{Spread_{i,t}} = \boldsymbol{\alpha} + \boldsymbol{\beta_1 Balance_{i,t}} + \boldsymbol{\beta_2 Leverage_{i,t}} + \boldsymbol{\beta_3 Membership_{i,t}} + \boldsymbol{\beta_4 Unprofitable_{i,t}} + \boldsymbol{\beta_5 MemberUnprofitable_{i,t}} + \boldsymbol{u_{i,t}}$$

Sample of 445 retail aggregator based foreign exchange traders for the period July 2008 to April 2013, including 519,152 round-turn transactions. The month a member joined the network is excluded. Balance is the log of the mean daily account balance across all active member accounts. Leverage is the log of the leverage used in the transaction. Balance and Leverage are winsorized at the 1% and 99% levels. Membership is a dummy set to 1 for months in which an individual is part of the network. Unprofitable is a dummy set to 1 for individuals whose mean monthly trade returns pre-membership were in the bottom quartile. Profitable is a dummy set to 1 for individuals whose mean excess trade returns pre-membership were in the top quartile. Member-Unprofitable and Member-Unprofitable are interaction terms equal to Membership x Unprofitable and Profitable respectively. Results are from an Ordinary Least Squares (OLS) regression clustered on member with robust standard errors using month and currency pair fixed effects, and are expressed in terms of the bid/ask return value for the trade (always negative). Standard errors indicated in parenthesis below the coefficient values.
(* p<0.10; ** p<0.05; *** p<0.01)

Test	**Membership**	**Unprofitable**	**Member-Unprofitable**	**Profitable**	**Member-Profitable**
Intercept	-0.000146***	-0.000140***	-0.000140***	-0.000144***	-0.000144***
	(0.000031)	(0.000031)	(0.000032)	(0.000029)	(0.000029)
Balance	0.000001	0.000000	0.000000	0.000001	0.000001
	(0.000003)	(0.000003)	(0.000003)	(0.000003)	(0.000003)
Leverage	0.000003	0.000003	0.000003	0.000003	0.000003
	(0.000003)	(0.000003)	(0.000003)	(0.000003)	(0.000003)
Membership	0.000007	0.000008	0.000008	0.000008	0.000007
	(0.000008)	(0.000008)	(0.000009)	(0.000008)	(0.000009)
Unprofitable		-0.000009	-0.000012		
		(0.000015)	(0.000019)		
Mem-Unprof			0.000005		
			(0.000019)		
Profitable				-0.000028**	-0.000028**
				(0.000011)	(0.000013)
Mem-Prof					0.000001
					(0.000014)
Adjusted R^2	5.71%	5.83%	5.84%	6.65%	6.65%

Table 5.13

Implications of Centrality on Currency Pair Selection for Individuals in a Retail Forex Trader Social Network, with Month Fixed Effects

$$\begin{aligned} \boldsymbol{Spread_{i,t}} = \ & \boldsymbol{\alpha} + \boldsymbol{\beta_1 Balance_{i,t}} + \boldsymbol{\beta_2 Leverage_{i,t}} + \boldsymbol{\beta_3 Membership_{i,t}} \\ & + \boldsymbol{\beta_4 Unprofitable_{i,t}} + \boldsymbol{\beta_5 MemberUnprofitable_{i,t}} \\ & + \boldsymbol{\beta_6 NoFriends_i} + \boldsymbol{\beta_7 Closeness_{i,t}} \\ & + \boldsymbol{\beta_8 MemberUnprofitableClose_{i,t}} + \boldsymbol{u_{i,t}} \end{aligned}$$

Sample of 445 retail aggregator based foreign exchange traders for the period July 2008 to April 2013, including 519,152 round-turn transactions. Balance is the log of the mean daily account balance across all active member accounts. Leverage is the log of the leverage used in the transaction. Balance and Leverage are winsorized at the 1% and 99% levels. Membership is a dummy set to 1 for months in which an individual is part of the network. Unprofitable is a dummy set to 1 for individuals whose mean monthly trade returns pre-membership were in the bottom quartile. Profitable is a dummy set to 1 for individuals whose mean excess trade returns pre-membership were in the top quartile. Member-Unprofitable and Member-Unprofitable are interaction terms equal to Membership x Unprofitable and Profitable respectively. Closeness is the centrality social capital measure based on the estimated friend connections for the trader in that month. Member-Unprofitable-Close and Member-Profitable-Close are interactions terms which are calculated as the prior interaction terms x Closeness. Results are from an Ordinary Least Squares (OLS) regression clustered on member with robust standard errors using month and currency pair fixed effects, and are expressed in terms of the bid/ask return value for the trade (always negative). Standard errors indicated in parenthesis below the coefficients.
(* p<0.10; ** p<0.05; *** p<0.01)

Test	**Close**	**Unprofitable**	**Unprofitable-Closeness**	**Profitable**	**Profitable-Closeness**
Intercept	-0.000142***	-0.000138***	-0.000138***	-0.000140***	-0.000138***
	(0.000030)	(0.000031)	(0.000031)	(0.000028)	(0.000029)
Balance	0.000001	0.000000	0.000000	0.000001	0.000000
	(0.000003)	(0.000003)	(0.000003)	(0.000003)	(0.000003)
Leverage	0.000003	0.000004	0.000004	0.000003	0.000003
	(0.000003)	(0.000002)	(0.000002)	(0.000002)	(0.000002)
Membership	-0.000010	-0.000010	-0.000011	-0.000010	-0.000012
	(0.000009)	(0.000009)	(0.000009)	(0.000009)	(0.000010)
No Friends	-0.000017*	-0.000017*	-0.000017*	-0.000019*	-0.000020*
	(0.000010)	(0.000010)	(0.000010)	(0.000010)	(0.000010)
Closeness	0.000071***	0.000071***	0.000076***	0.000062**	0.000071***
	(0.000025)	(0.000023)	(0.000024)	(0.000025)	(0.000026)
Unprofitable		-0.000012	-0.000012		
		(0.000018)	(0.000018)		
Member-Unprof		0.000009	0.000014		
		(0.000017)	(0.000020)		
Mem-Unprof-			-0.000030		
			(0.000058)		
Profitable				-0.000034***	-0.000034***
				(0.000012)	(0.000012)
Member-Prof				0.000016	0.000027*
				(0.000012)	(0.000015)
Mem-Prof-Close					-0.000094*
					(0.000051)
Adjusted R^2	8.27%	8.36%	8.39%	9.00%	9.18%

Table 5.14

Implications of Brokerage Position on Currency Pair Selection for Retail Forex Traders in a Social Network, with Month Fixed Effects

$$\begin{aligned}\boldsymbol{Spread_{i,t}} = {} & \boldsymbol{\alpha + \beta_1 Balance_{i,t} + \beta_2 Leverage_{i,t} + \beta_3 Membership_{i,t}} \\ & \boldsymbol{+ \beta_4 Unprofitable_{i,t} + \beta_5 MemberUnprofitable_{i,t}} \\ & \boldsymbol{+ \beta_6 NoFriends_i + \beta_7 Betweenness_{i,t}} \\ & \boldsymbol{+ \beta_8 MemberUnprofitableBetween_{i,t} + u_{i,t}}\end{aligned}$$

Sample of 445 retail aggregator based foreign exchange traders for the period July 2008 to April 2013, including 519,152 round-turn transactions. Balance is the log of the mean daily account balance across all active member accounts. Leverage is the log of the leverage used in the transaction. Balance and Leverage are winsorized at the 1% and 99% levels. Membership is a dummy set to 1 for months in which an individual is part of the network. Unprofitable is a dummy set to 1 for individuals whose mean monthly trade returns pre-membership were in the bottom quartile. Profitable is a dummy set to 1 for individuals whose mean excess trade returns pre-membership were in the top quartile. Member-Unprofitable and Member-Unprofitable are interaction terms equal to Membership x Unprofitable and Profitable respectively. Betweenness is the log of 1 plus the brokerage social capital measure based on the estimated friend connections for the trader in that month. Member-Unprofitable-Between and Member-Profitable-Between are interactions terms which are calculated as the prior interaction terms x Betweenness. Results are from an Ordinary Least Squares (OLS) regression clustered on member with robust standard errors using month and currency pair fixed effects, and are expressed in terms of the bid/ask return value for the trade (always negative). Standard errors indicated below the coefficients.
(* p<0.10; ** p<0.05; *** p<0.01)

Test	Between	Unprofitable	Unprofitable-Betweenness	Profitable	Profitable-Betweenness
Intercept	-0.000136***	-0.000131***	-0.000131***	-0.000134***	-0.000134***
	(0.000030)	(0.000031)	(0.000031)	(0.000029)	(0.000029)
Balance	0.000000	-0.000001	-0.000001	0.000000	0.000000
	(0.000003)	(0.000003)	(0.000003)	(0.000003)	(0.000003)
Leverage	0.000004	0.000004*	0.000004*	0.000004	0.000004
	(0.000003)	(0.000002)	(0.000002)	(0.000002)	(0.000002)
Membership	-0.000001	-0.000001	-0.000001	-0.000002	-0.000002
	(0.000007)	(0.000008)	(0.000008)	(0.000008)	(0.000008)
No Friends	-0.000020*	-0.000020**	-0.000020*	-0.000022**	-0.000022**
	(0.000010)	(0.000010)	(0.000010)	(0.000010)	(0.000010)
Betweenness	0.000432***	0.000432***	0.000430***	0.000399***	0.000400***
	(0.000069)	(0.000069)	(0.000068)	(0.000070)	(0.000070)
Unprofitable		-0.000015	-0.000015		
		(0.000018)	(0.000018)		
Member-Unprof		0.000009	0.000005		
		(0.000018)	(0.000018)		
Mem-Unprof-Betw			0.005155*		
			(0.002949)		
Profitable				-0.000034***	-0.000034***
				(0.000012)	(0.000012)
Member-Prof				0.000015	0.000016
				(0.000012)	(0.000012)
Mem-Prof-Betw					-0.008640***
					(0.002497)
Adjusted R^2	8.88%	9.01%	9.11%	9.65%	9.69%

Chapter 6: Observer Effects on Trader Performance

6.1. Introduction

In Chapter 5 the focus is on the transmission of information between and amongst financial markets participants and the potential impact of both the receipt/processing of that information and those interactions on investor activity and performance. In this chapter the focus shifts to looking at things from the reverse perspective – the influence on investors of their transmission of information and the realization that their behaviour and actions in the market are observable by others. This line of examination is motivated in part by an anecdote shared with me by one of the managers of the retail social network which is the source of the data used in this thesis.

In Section 3.2 of Chapter 3 a trade copying process is described by which the transactions of one or more members of the social network could automatically be copied in the accounts of other members. The “leaders” whose trades got copied were selected by the network’s management based on prior performance and suitability for replication. In one instance a trader selected to be a leader saw his performance completely fall apart once he went live and started having his trades copied. Things did not improve with time, so the managers eventually pulled him from his leader position. Immediately after that, his performance resumed its prior excellence.

As researchers, it would be easy to dismiss a case like this as simply reflecting a random fluctuation in investor performance. In talking with this trader, though, the management learned that he felt an anxiety while being a leader he did not feel when simply trading for himself – an anxiety which negatively influenced his trade decision-making. This is despite the fact that he was not required or requested to do anything different than what he had been doing before being accepted into the copying program. In fact, the whole idea was that he just keep doing what he was doing!

There are two potential ways of examining the anxiety response described by this trader. On the one hand, he may have become anxious about the idea that his performance was influencing the returns of others. This is the sort of reaction one might witness in new money managers and other professionals given fiduciary roles for the first time. The other is that the mere idea his trades and/or performance were being closely observed may have influenced his mental state, leading to impaired decision-making. While both conceptual ideas are worth consideration and research, it is the latter which is the focus of this chapter in the context of social network participation.

The idea that being observed can change behaviour is far from a new concept. There is a considerable literature in psychology and related areas on the subject (Zajonc, 1965, Wicklund and Duval, 1971, Adair, 1984, Munger and Harris, 1989, Hartmann and Wood, 1990, Leary and Kowalski, 1990, Seta and Seta, 1995, Grant and Dajee, 2003, Uziel, 2007). From a business perspective, a large portion of the management literature could be said to focus on the area of performance under observation. Ellingsen and Johannesson (2007) provide one example with respect to employees being motivated in their behaviours by the desire to be respected by their co-workers and peers, as well as their employers. While the employer aspect may not feature when considering a social network of individual investors, the respect of one’s peers certainly does.

The finance literature thus far only barely touches on the thought processes of individual investors under observation. While the herding, peer, and developing social effect literature documented in Chapter 5 demonstrates a realization of the influence on Investor B of what they see Investor A doing, the research does not yet look meaningfully at the decision-making of Investor A with regards to what Investor B will glean from their activity and performance. Where it does so, the focus is either on professionals (Lakonishok et al., 1991, Morey and O'Neal, 2006) or on filtered sharing (Han and Hirshleifer, 2015).

The aim of this chapter, therefore, is to expand the finance literature in the area of individual investor activity under observation by examining members of a trader social network. Doing so may provide an understanding of the potential impact of regulatory moves toward increased transparency on individual investor activity and performance. In a related fashion, it could also lead to greater understanding of the influence of technological developments which facilitate the observation of investors by their peers via social networks, performance sharing websites, etc.

The remainder of this chapter is structured as follows. Section 6.2 reviews the prior literature and develops the primary hypotheses of the chapter. Section 6.3 provides documentation of the data and methodologies being employed in the research, with Section 6.4 containing the analysis. Section 6.5 concludes and presents considerations for future research.

6.2. Literature Review and Hypotheses

6.2.1. Observer effects

In the social sciences it is understood that the act of observing an individual can influence their behaviour. In a review of the relevant literature in the area of applied behavioural analysis, Hartmann and Wood (1990) describe the concept of reactivity whereby the presence of an observer introduces a novel stimulus to the observed, thereby resulting in an alteration of their behaviour. It does not necessarily even matter if an individual is actually being observed, only that they believe they might be. This is the basis of the idea of the "panopticon effect" whereby the belief that one is constantly under potential surveillance influences one's behaviour (Reiman, 1995).[83]

Hartmann and Wood (1990) go on to outline five factors which are suggested to contribute to reactivity. Most of these factors relate to the framework in which a subject is being observed. They include the individual characteristics of the subject on the presumption that certain types of individuals - those who are naturally more open and/or confident, those who are oblivious to being observed (like young children), and those who are insensitive – are less likely to be influenced by observation. For example, Grant and Dajee (2003) find differences between introverts and extraverts in performance of simple math tasks based on audience. Similarly, Uziel (2007) indicates differences in how individuals react to an audience based on personal characteristics such as positive/negative orientation and self-esteem levels.

The factors of reactivity also include the degree to which the subject is consciously aware of being observed, who is doing the observing, and how they are presented. An example of this comes from Seta and Seta (1995) who find differences in how individuals perform and the way their task interest varies depending on the degree to which the audience is aware of the observed individual's prior performance. The expressed or suspected motivation for the

[83] The mirrored or blacked out coverings over security cameras in stores are variations on the panopticon idea in that one can never know whether they are actively being observed or not.

observation is also a consideration. One could think of these factors as relating to the degree of influence observation has on the subject.

The remaining factor is the valence of the behaviour, which speaks to what actually changes in the subject. The implication here is that observation will tend to encourage socially appropriate or desirable behaviours while also tending to discourage undesirable or inappropriate ones - or those that otherwise would be considered private. An example is provided by Munger and Harris (1989) in their finding of increased restroom hand-washing by women in the presence of an observer. The research even goes so far as to suggest that simply the idea of being watched, such as the presence of the image of a set of eyes, can influence behaviour on this basis (Bateson et al., 2006).

The behavioural change need not be something related to social acceptability, however. The now famous "Hawthorne Effect" in which workers in a plant were theorized to be more productive while being observed speaks potentially to two alternative ways of considering observer effects.[84] One is that generally speaking subjects will do what they think will make them look best, be that being more productive for their managers in the Hawthorne case or more likely to adhere to social norms in the hand-washing one noted above. The other is that observation can improve subject satisfaction – at least when the observer holds a certain status relative to the subject.[85]

The presence of observer effects motivates two potential questions with respect to investors and traders. The first is the sort of behavioural change to be expected in those being observed. The second is whether there is any difference in the type or degree of behavioural change seen based on the manner of the observation taking place.

At the institutional level, observation is a fact of life for traders and investors. Compliance and regulatory considerations mandate varying levels of direct and indirect oversight. For some, such as individual dealers at banks and other financial institutions, the observation can be highly granular. Their transactions could be monitored throughout the day and the execution of them may be directly observed by co-workers and/or managers in real time. In the case of rogue traders, there is generally a specific effort to circumvent

[84] See Adair (1984) for a review of the research related to the Hawthorne Effect.
[85] One of the Hawthorne theories developed was that increased worker productivity related to the satisfaction of knowing management paid attention to them.

observation to mask one's unauthorized trading or hide losses and/or a failure in oversight by management.[86] At the other end of the observational frequency spectrum are funds mandated to file periodic (e.g. quarterly) reports of holdings, which may be subject to so-called "window dressing" (Lakonishok et al., 1991, Morey and O'Neal, 2006).

Compliance and regulatory oversight are not the only sources of trader and investor observation. There is also the direct observation of trading activity by other market participants. From this point of view, the activity in the market by one participant can be information used by another in their own decision-making. This potentially could be the basis for the type of intentional herding described by Bikhchandani and Sharma (2000), and the general idea of an information cascade, or alternatively an information contagion, as discussed in Chapter 5. Traders are informed by what they specifically see being done by market participants who are earlier actors than themselves. Hasbrouck (1988) provides evidence for this, in particular finding that larger trades are more informative than smaller trades, which speaks to the desirability of watching the bigger market players.

Direct observation by other market participants could also be viewed from an adversarial perspective, to use the Treynor (1999) terminology, in that one trader's activity could be used advantageously by others above and beyond any information it might provide from a pricing perspective. For example, if one trader knows another trader's positional exposure or intentions, they might be able to take advantage of that in the form of more favourable pricing in a transaction between the two, or being positioned ahead of a price move driven by what the other will do in the future. Direct observation of competitor trading is possible in open-outcry markets,[87] though they are few and far between now. The focus has shifted to electronic platforms, which still provide a level of participant visibility. Institutional level traders and investors are already incentivized from a cost perspective to limit the impact of their activities on price, which is a large element of the research into optimal order placement strategies (Keim and Madhavan, 1995, Cont and Kukanov, 2013). Above and beyond the financial costs, however, large market participants are also

[86] See Wexler (2010) for a review of the rogue trader literature.
[87] See Schwager (1989) for anecdotal evidence of the competitive use of fellow trader activity among "pit" traders.

incentivized from an adversarial perspective to mask their market activities to avoid others gaining a competitive advantage.

Returning to the question of observation effects, in the case of institutional investors there are therefore answers to both the question of what changes may be expected under observation and the potential impact of the observational structure on those behavioural changes. What of individual investors, though?

Because individuals operate almost exclusively through intermediaries, the direct visibility of their actions generally is virtually nil. Further, as per Hasbrouck (1988), their trades are individually of much less informational value with regards to price, if any at all, so there is little incentive for other market participants to attempt to observe them directly. Moreover, in order to observe the market activity of a given individual, said individual must explicitly share their activity. Han and Hirshleifer (2015) focus on this sharing from the perspective of what individuals provide to others and the impact that has on the recipients in a social context. This is based on the assumption that market participants will tend to shade what is shared in a way which casts themselves in a favourable light by perhaps downplaying or omitting their failures. The result is the propagation of trading strategies which tend to have attention-inducing outcomes, meaning those with a high volatility of returns.

The reasonable assumption is that individuals are not simply making all of their trading activity publicly available – at least not in real time. For most of the history of the financial markets it was effectively impossible to share this sort of data in a timely fashion. Modern technology, however, has changed that. Now it is possible for essentially any market participant to share their trading and investing activity with others as it happens. It is the behavioural impact potentially motivated by doing so which is now the question.

Individual investors and traders do not have the regulatory or compliance oversight to motivate rogue trader or window dressing type of behaviour. The existence of social networks, chat rooms, forums, and other vehicles by which they meet and exchange ideas suggests that at least some do not see themselves as being in direct financial competition with others. Individually their trades are of little value to others from a pricing perspective,[88] so there is no

[88] Though taken in aggregate there is a potential indication of market sentiment.

need to hide or mask their activity to avoid it being used against them the way it might be for a professional money manager. What that would seem to leave is behavioural change motivated by perceived reputational impact.

6.2.2. Impression management

Leary and Kowalski (1990) provide an oft-cited review of the impression management literature. This is a subject area which explores the way individuals seek to present themselves to control how they are seen by others – their reputation. The authors break impression management down into two processes - impression motivation and impression construction. The former is the process by which individuals find it desirable to attempt to control how others see them. The latter is the process by which motivated individuals actually seek to go about shaping how they are seen. In turn, each of these processes can be broken down into factors.

In the case of impression motivation, the drivers in question are social and material outcomes, self-esteem maintenance, and development of identity. Essentially, someone may become motivated to engage in impression management because they desire the benefits of it such as approval, friendship, assistance, etc.; because they are looking for self-esteem enhancing reactions; and/or because they are seeking to develop a certain identity. With respect to the outcomes motivation, the finance literature has touched on the idea that analysts (Welch, 2000) and money managers (Scharfstein and Stein, 1990, Hong et al., 2005) may attempt to shape how they are perceived with respect to career development and other perception considerations. They do so by making decisions influenced by what they see their peers doing rather than based on what they think is the right performance choice (stock forecast, portfolio investment, etc.), potentially resulting in herding effects.

When considering individual traders and investors, one can easily understand how the perception of being a savvy market participant among one's peers could relate to all three factors and thereby motivate an individual toward impression management in a social context. This is even more the case when one's activities are public. To quote Leary and Kowalski (1990):

"Overall, the more public one's behavior, the more likely one is to be concerned with how it appears to others, and the more motivated one will be to impression-manage… Publicity affects impression motivation because public

behaviors are more likely to be relevant to the accomplishment of one's goals than are private behaviors. Indeed, all three of the motives we have described are more likely to be fulfilled when one's behaviors are public rather than private."

On this basis, an individual making their trading activity public is more likely to be involved in impression management the more visible that activity is to others – or at least how visible it is perceived to be. How one then goes about managing that impression is said to be based on five factors. These are self-concept, desired and undesired identity images, role constraints, target values, and current or potential social image. Of the quintet, the second and the fifth would seem to be the most relevant in the current context. They speak to individuals seeking to present themselves in the most (least) desirable (undesirable) fashion from the perspective of those whose impression is perceived to matter, along with how they currently see themselves regarded by others and how they would like to be regarded in the future.

The question then becomes what sort of behaviour an individual seeking to manage their impression of being a savvy market participant - or at least not a completely clueless one – would be observed. The research thus far with respect to investors in a position to share their trading activity with others publicly is unfortunately more focused on the information content of investor interactions (Antweiler and Frank, 2004), their interaction structure (Gu et al., 2008), and their influence on behavioural effects (Mizrach and Weerts, 2009, Park et al., 2013). Mizrach and Weerts (2009) in particular analyse trades posted in real-time, which most aligns with the question of the behavioural implications of being fully public, but their study lacks data for the included traders from before they became involved in the chat room observed. As such, it is not possible to ascertain the degree, if any, to which the traders may have changed their behaviour upon entering the chat room – or in fact if they did other trades outside the chat room (unobserved) which were of a different nature than those reported inside it.

The closest the research at the individual investor level comes to addressing the impression management question to-date is Han and Hirshleifer (2015). In that research the authors propose a self-enhancing transmission mechanism driven by what could be described as a "bragging" type of interaction between socially connected investors through which individuals are motivated to selectively share their greatest successes. The result is the propagation of high variance trading strategies through a network. Simon and Heimer (2014) test this concept empirically and find support for this type of transmission taking place when examining traders in an online social network. Heimer (2014b) works from a similar conceptual framework in terms of looking at social interactions, but with a different type of outcome analysed (an increased impact of disposition effect influences). The problem in both cases is the concentration on what investors say they are doing (or have done) rather than on what can actually be seen of their actions and performance, however. The question at hand is whether, and if so how, individuals change their actual trades when they know or believe they are being observed by others with no possibility of filtering.

There are two ways of approaching this issue. The first is in terms of the decision-making leading up to the trades which are then executed. This includes the selection of the instrument(s) to be traded, the market-timing strategy employed, and the degree of leverage used (how large a trade is relative to account size). While the specific strategy employed cannot be observed directly by simply looking at transactional data, it is possible to examine instrument selection and potentially leverage use. The latter, in particular, is a meaningful consideration where it may signal overconfidence. This is addressed in Section 6.2.4.

The second way to approach the issue is in terms of what happens once the trade is entered. That essentially is the question of when the trade is exited. This is necessarily related to the selection of market-timing strategy, which is not directly observable. From a behavioural perspective, the disposition effect is directly related to the timing of position exits, however.

6.2.3. Disposition effect

Shefrin and Statman (1985) theorize what has become known as the disposition effect based on the concept of loss aversion put forth by Kahneman and Tversky (1979). The disposition effect suggests that investors are quick to take profits for fear of giving back some or all of their gains, while at the same time are slow to exit losing trades in hopes they will turn around. Experienced market participants are well aware of this effect, at least informally, which leads to the commonly shared advice to “Cut your losers and let your winners run.”

Odean (1998a) empirically tests for the disposition effect among investors, finding evidence for it in account holders of a discount stock broker. It is also documented among Finnish investors by Grinblatt and Keloharju (2001), among day traders by Jordan and Diltz (2004), among professional traders by Coval and Shumway (2005) and Locke and Mann (2005), among Taiwanese investors by Barber et al. (2007), and among retail foreign exchange traders by Nolte and Voev (2011).

In a social context, Heimer (2014b) finds that increased interaction between traders in a social network results in an increase in the observation of the disposition effect among retail forex market participants. That study, however, only looks at trader visibility from the perspective of the exchange of messages, which is a filtered form of publicity. It fails to account for the fact that the actual unfiltered trading activity of those in the study is visible in real-time to other network members, and potentially beyond.

Barberis and Xiong (2009) extend the conceptual framework with respect to the disposition effect to demonstrate that realized returns are more subject to it than are unrealized ones. Meaningfully for the current discussion, Barberis and Xiong (2012) go one step further with a broader examination of the concept of realization utility, which captures the utility - financial or otherwise - received immediately by an investor upon exiting a position. Viewing trade disposition in this fashion goes beyond loss aversion as the motivating factor behind being quicker to take profits than losses, one which comes about from investors thinking not in terms of overall returns, but rather as each investment being a discreet event - an “investing episode” to use the authors’ terminology. This has implications from an impression management perspective, as the utility derived at the closure of a trade could in part be the perceived benefit to one’s social reputation within an investor peer group, especially since individual transactions are more frequent signal points to others than would be a simple reporting of period returns. Further, automatically shared trades are more frequent signal points than are those shared via chat room discussion and other forms of manual trade sharing, which is subject to filtering. It is suggested by the authors that less sophisticated investors would more likely fall victim to such a mind-set.

Ben-David and Hirshleifer (2012) provide a number of challenges to the disposition effect theorizations, pointing to other potential explanations beyond realization preference. Interestingly for the current discussion as it relates to foreign exchange market speculators, the authors find that investors in the case of short holding periods exhibit a higher likelihood of selling larger losers than smaller ones, however. They indicate this is in contrast to the idea that investors avoid realizing large losers, but by definition at some point a loss must be realized. If there is indeed an aversion to taking a loss, then one would least expect small losses to be taken as they would be expected to be viewed by investors as the types of losses that could be reversed.

Regardless of the latter point, if there is evidence that investors exhibit a different level of disposition effect when being observed than when not being observed, then it would be potential evidence for at least some realization preference at work – in this case in the form of impression management. What needs to be considered is in what form changes in disposition can be expected, and in whom they would most likely be seen.

6.2.4. Overconfidence

As noted in Section 6.2.3 above, leverage is part of the pre-entry decision-making process for each trade in that it is directly linked to the size of the position in question. In Chapter 4 a connection between investor performance and overconfidence is drawn, using leverage as a key metric. It extends on the prior literature's assertion that overconfidence drives increased trading activity (Odean, 1998b, Barber and Odean, 2000, Gervais and Odean, 2001) and goes one step further to link overconfidence to impaired returns not just on the basis of additional costs driven by that larger transactional volume, but also worsened market timing performance based on the idea that it indicates biased decision-making (Kahneman and Riepe, 1998, Burks et al., 2013). What it does not address in a meaningful fashion, however, is the potential source(s) of overconfidence.

In looking at social network participation, Chapter 5 does broach the subject of what can motivate investor overconfidence, and by extension increased leverage use, however. Both Barber and Odean (2001b) and Barber and Odean (2002) draw a connection between greater access to information and overconfidence, the idea being that greater availability of news and data can lead to overestimation of one's knowledge. De Carolis and Saparito (2006) narrow the focus to social network participation as a source of that information, particularly concentrating on network position (social capital) which speaks to the speed of access and the degree of trust involved in information acquisition. What investors do with the information they gather from their social contacts is the subject of both Gu et al. (2008) and Park et al. (2013) who find confirmation bias at work. Investors seek to affirm their prior beliefs, contributing to overconfidence. Unfortunately, the analysis in Chapter 5 finds little to support the argument that social networks motivate overconfidence – at least from an information perspective. In fact, if anything the findings tended to point in the opposite direction.

That said, there is the potential for social network participation to drive overconfidence from an information transmission rather than reception perspective. It is one which is closely tied to impression management as described in Section 6.2.2. In fact, Burks et al. (2013) find that it is "…*the process of communicating judgements about one's relative performance to others*…" which is the prime driver of individual overconfidence. This is instead of Bayesian updating based on signals of one's ability or information acquisition based self-deception. The former is the general basis for how much of the foundational overconfidence literature in finance has been developed (De Bondt and Thaler, 1995), while the latter links to the social network research noted above - providing a potential explanation why no results of note were observed in Chapter 5 with respect to increased overconfidence among network members.

Generally speaking, the type of communication central to the Burks et al. (2013) findings is filtered in that individuals may pick and choose the information about their activities and performance which presents them in the best light. This involves the sort of "selective omission" described by Leary and Kowalski (1990) with respect to impression management. As such, a link is drawn between investor overconfidence and the activities involved in impression management. Putting it simply, investor overconfidence is increased through the communication of one's relative performance, not simply by receiving indications of it as might be expected.

What of the case where an objective, unfiltered indication of relative investor performance is available, however? That presumably would bring in to focus the Bayesian updating process discounted by Burks et al. (2013) as having any impact on investor overconfidence. In such a structure, no overconfidence-driven influence on performance would thus be expected because the “look how great I am” type of communication mentioned above is superfluous. A relatively strong performer would not need to communicate their performance to others because it would already be there for all to see. In fact, any selective omission employed by an individual by way of impression management could easily backfire because of the availability of the unfiltered information, resulting in a reduced level of social credibility and status.

The question is then whether the unfiltered information transmitted by socially interactive investors (actively or passively) acts in the same fashion as the filtered communication with respect to driving overconfidence. If such information transmission reinforces (or even enhances) what an investor perceives to be their superior status within the network, then this could indeed be the case. This would tie in with the experimental findings of Heath and Tversky (1991) that those who perceive themselves to be expert in a subject will tend to place greater weight on in their own judgements related to that area, resulting in higher levels of overconfidence.

Generally speaking, in a social network context the degree to which one’s communication is disseminated relates to how many network connections (friends) an individual has at any given time. One could go a step further and introduce the idea of network position and social capital as discussed in the previous chapter, but from a status and visibility perspective a friend focus is easier for an individual to appreciate and recognise than their network position. It speaks to how many others a member knows for sure are in their network and who will receive an unfiltered, uninfluenced transmission of information. The greater the number of friends, the larger the audience and the higher the observability, per Leary and Kowalski (1990), and the greater the communication of information which could be used to form judgements to motivate overconfidence, as per Burks et al. (2013).

6.2.5. Hypothesis development

As noted in Section 6.2.3, one of the questions which needs to be addressed is what category or categories of individuals would be most expected to employ impression management tactics in an individual trader context. Leary and Kowalski (1990) offer some considerations to that end in that impression management is said to be motivated by social benefits (approval, friendship, etc.), because one seeks enhanced self-esteem from others’ reactions, and/or because they wish to develop a desirable identity. Taking things a step further, it is worth considering as well the potential impact of impression management activities from the overconfidence perspective outlined in Section 6.2.4.

Among a collection of socially connected traders, one group which stands out as being motivated toward impression management based on these considerations is individuals reasonably considered to be seen as, and/or view themselves to be, the best market-timers – those who make the best trades, on average. Their position at the top of the heap provides them potential social benefits (which may include financial rewards) and enhanced self-esteem. It may also relate to an identity which they wish to retain or develop. As members of this group have reason to want to retain a perception by others as savvy traders, they have more to lose from being observed than would likely be the case for other groups. Since these sophisticated traders clearly have high status, and can use communication to reinforce that, they are also subject to potential increased overconfidence. The combination makes them a group worthy of examination.

A second group worth considering on the basis of developing an identity is unsophisticated traders - those who have been relatively big losers in the market. Such a group would be desirous of becoming good traders, not just from the perspective of returns, but also in terms of how they could judge themselves and be judged by others. This is particularly true in the context of a social network where trading savvy could translate into social status. That then speaks to the social benefits motivation above. Further, self-esteem enhancing reactions from their peers would serve to help develop the “good trader” identity they seek. This group, especially to the extent they are likely inexperienced, is also generally one which is expected to exhibit more behavioural influence on their trading, as per Barberis and Xiong (2012). That makes it a good candidate for observing potential impression management.

Unfortunately, examination of this unsophisticated group is challenging because part of the educational process for such individuals is to adapt trading habits which are also the sort one might expect to see exhibited by those attempting to manage their public impression (i.e. doing things “good” traders do). Further, the unsophisticated group is unlikely to have the same sort of impression management influence on overconfidence as would be expected amongst sophisticated members since they would struggle to see themselves as being relatively savvy. As such the focus of this chapter will be on the sophisticated traders described above.

Having identified traders most likely to be motivated to manage their impression, the question shifts to the manner in which that is attempted with regards to their visible trading activity. As mentioned earlier, there are only a few ways this can be accomplished. The first is to alter the instruments one is trading in a manner which one believes demonstrates a desirable level of sophistication. There are two ways this might go. The first is to increase focus on the lowest “cost” instruments, which also tend to be the ones with the greatest liquidity and lower levels of volatility. The second way a trader might think about the instrument question in terms of impression management is to seek to move away from “common” instruments as a way to distance themselves from the herd. This presents the first hypothesis.

Hypothesis 1: Sophisticated traders change the instruments they trade as they are more observed (or judge themselves to be so).

A second factor in prospective impression management is in the disposition phase after a trade has been entered. The excess return of trades is heavily influenced by the market-timing strategy, which will be discussed momentarily, but the final result may also be influenced by a set of potential desires, one of which could be the desire to be proven “right” by showing a profit or to otherwise demonstrate trading savvy. This could trigger a change in the holding period of winning trades. Those who seek to underline their expertise may seek to hold positions longer, counter to the “exit too early” element of the disposition effect. Alternatively, it is possible that loss aversion could actually increase, resulting in quicker exits. On that basis, the next of this chapter’s testable hypotheses may be stated.

Hypothesis 2: Sophisticated traders will be increasingly influenced to change the holding period of their winning trades the more they are observed.

The counter to cutting winning trades quickly from a disposition effect perspective is holding on to losing trades longer. Among sophisticated traders the admonition “cut your losses and let your winners run” is well known. As such, a member of that group looking to demonstrate their trading savvy is likely to want to demonstrate they are not like other traders by avoiding large losses. This may have the result of seeing them exit losing trades more quickly than otherwise would be the case. To a degree, this could also be something linked in with the idea of being seen as more being more prudent. Again, however, observation may actually increase loss aversion, resulting in longer holding periods for losing positions. As such, the third hypothesis of this chapter may be developed.

Hypothesis 3: Sophisticated traders will see greater changes in the time they remain in losing trades the more they are observed.

The third area of influence where observability and having an audience is likely to have an impact is in leverage use, which is part of the position size pre-trade decision-making process. On the one hand, it could be theorized that increased prudence may be a motivation of increased observability. That would lead to lower leverage use. A change in this type of attitude is likely to already be expressed in the selection of tradable instrument, though. As such, it is worth turning the leverage focus to use it as an indication of increased overconfidence based on the ideas developed in Section 6.2.4. On that basis it would be expected that a greater audience size, implying a higher level of outgoing judgement communication, would result in greater leverage use. That provides the basis for the next hypothesis of this chapter.

Hypothesis 4: Sophisticated traders increase leverage as their perceived level of observation increases.

The final factor available for impression management influence is the market-timing strategy employed by the trader. This cannot be directly observed, but through analysis of outcomes in the form of realized excess returns, changes may be noted. If a trader alters their approach to market timing as a function of an impression management desire, it likely means they are shifting to a less optimal approach – at least from their own perspective. This potentially would be linked to increased overconfidence as per the findings of Chapter 4. As such the following hypothesis can be developed:

Hypothesis 5: Sophisticated traders demonstrate increasingly lower excess returns as they are more observed.

These hypotheses are tested in Section 6.4 below.

6.3. Data & Methodology

The data used in the analysis of Section 6.4 below is the same as that employed in Chapter 5, as documented in Section 5.3. However, in this chapter only the individual transactions information is utilized. The aggregated monthly values are not required. For the purposes of comparability of the results between this chapter and the last, the month a member joined the network continues to be excluded despite being able to more finely parse things at the transaction level by date. This also serves to minimize potential network influence issues related to lags between registration when an individual could conceivably have access to certain public network information (recalling from Chapter 3 that some members opted to allow their profiles to be fully accessible) and full membership activation through the linkage with one's brokerage account.

The focus of the hypothesis testing to follow is the same set of "profitable" traders defined at the beginning of Section 5.4 from last chapter. That is the group of individuals who comprise the top quartile based on their mean trade excess return for the transactions they did prior to entering the network (market timing performance). It may be possible to use an alternative method to derive a group of sophisticated traders. In this case, however, the quality of most value for testing purposes is demonstrated skill in making good market calls. The social network from which the data is extracted is one where traders can only directly observe each other's entry and exit points - not the size of a position or its actual return. That being the case, it makes most sense to analyse individuals who are likely to be seen as and/or perceive themselves to be good at getting in and out of the market in a profitable fashion.

Keeping to the subject of trade excess return, unlike the case in Chapter 5 where it is only used for classification purposes, in this chapter it also features as a specific metric of study (see Section 6.4.4). It can be thought of as comparable in this case to the analysis of average deleveraged return from Section 4.4.6 of Chapter 4. The only conceptual difference between the two, aside from one being a mean, is that the excess return value excludes spread whereas the deleveraged return does not. They both serve the same purpose in focusing on trader market timing performance.

Addressing the primary theme of observability for this chapter, once again a member's friend connections are of key consideration in the analysis which follows in Section 6.4. While the last chapter mainly incorporated the estimated friend counts as the basis for the determination of network position measures, in this chapter they are a primary feature and used directly. Refer to

Section 5.3.2 for the estimation procedure employed. In this case the social capital measures are not utilized, however. Individuals are likely to struggle to conceptualize their position in a large social network beyond immediate awareness of their friends, and potentially some idea to whom their friends are linked as a second level consideration.

Because the focus is directly on estimated friend counts, attention must be paid to extremely connected individuals, as their inclusion could alter the outcome of the analysis. In this case, as noted in Chapter 5, there are two members with far more friends than any others. Among the 445 network members in question, 99% have 119 or fewer friends. One of the two high friend count individuals in question has over 1000 friends as of the May 2013 indication, while the other has more than 500. This makes them strong candidates for being network administrators, at least one of whom was known by myself to connect with everyone who joined the network during the early period of its growth (assuming they were willing, of course). As such, they represent both a potential outlier influence on the data as well as being individuals for whom observability was viewed in an entirely different context than for the majority of members. They are therefore excluded from the forthcoming analysis, resulting in a dataset of 443 members and over 488,000 transactions (analysis of their inclusion is discussed in Section 6.4.5).

6.4. Analysis

6.4.1. Does visibility influence trading instrument selection?

The first hypothesis of this chapter addresses the idea that traders may change the instruments they trade when they are subject to observation. This can be evaluated in the context of foreign exchange trading by examining the currencies and currency pairs being traded. There are two ways to do so. One is to examine the mean bid/ask spread of the trades they trade, which provides an indication of the liquidity and volatility of the composition of exchange rates in which individuals are active. Another is to analyse the actual fraction of trades done in specific currencies and/or currency pairs.

Table 6.1 provides descriptive statistics which start to address the question. Panel A of the table compares to Panel B from Table 5.1 from the last chapter. Panel B of Table 6.1 focuses on the profitable traders who are the main subject of the analysis herein. The means comparison (unpaired T-test) shows that these traders generally shift toward a more conservative approach once in the network. They increase their focus on trading in the euro and the US dollar, the two most active and liquid currencies. At the same time, they decrease the frequency with which they trade more exotic currency pairs – those which include no more than one of the so-called majors (USD, EUR, GBP, JPY, AUD, CAD, CHF). The combined result sees them trading currency pairs with a narrower mean bid/ask spread.

It may be the case that simply joining the network is enough to trigger an observation effect, which could be what the results from Table 6.1 are picking up with respect to profitable traders. Leary and Kowalski (1990), though, indicate that an observation effect is greater the greater the observation, or at least the perception of observation. In a social network setting it is the members with the most friends who are expected to be the most observed. As such, it should be the case that greater effects are seen amongst those with the most friends. To that end, it is possible to test Hypothesis 1 by develop the following model which captures variation based on friend connections:

$$\begin{aligned} Spread_{i,\mathrm{t}} = \ & \alpha + \beta_1 Leverage_{i,\mathrm{t}} + \beta_2 Membership_{i,\mathrm{t}} + \beta_3 Profitable_i \\ & + \beta_4 MemberProfitable_{i,\mathrm{t}} + \beta_5 Friends_{i,\mathrm{t}} \\ & + \beta_6 MemberProfitableFriends_{i,\mathrm{t}} + u_{i,\mathrm{t}} \end{aligned} \tag{6.1}$$

Where

$Spread_{i,\mathrm{t}}$ is the return equivalent of the bid/ask spread for position *t* executed by Trader *i*.

$Leverage_{i,\mathrm{t}}$ is the log of the leverage used by Trader i in position *t*.

$Membership_{i,\mathrm{t}}$ is a dummy for network status of Trader *i* at the time position *t* is entered (member = 1).

$Profitable_i$ is a dummy set to 1 if Trader *i* is among the top quartile of traders based on pre-membership mean excess trade returns.

$MemberProfitable_{i,\mathrm{t}}$ is an interaction term equal to $Membership_{i,\mathrm{t}}$ x $Profitable_i$.

$Friends_{i,\mathrm{t}}$ is 1 + the log of the estimated number of friends connects for Trader *i* in the month when position *t* is entered.

$MemberProfitableFriends_{i,\mathrm{t}}$ is an interaction term equal to $MemberProfitable_{i,\mathrm{t}}$ x $Friends_{i,\mathrm{t}}$.

The regression also clusters on member to account for correlation of residuals at the individual trader level. Robust standard errors are derived to address heteroscedasticity and non-normality. Leverage is winsorized at 1% and 99% to limit the influence of outlier observations on the results.

The model includes trade bid/ask spread as an indicator of a change in the distribution of currency pairs traded by a given member. Trade level leverage is included as the other decision point a trader has when entering a position beyond that of market timing. At the individual transaction level an aggregate control factor such as trade frequency must be excluded because each trade is actually a contributory factor toward period trade count. Trade duration for any given position is a function of factors outside the trader’s control (most specifically, market action). Account balance is similarly not something under the immediate control of the trader at the time a position is entered, so it has been left out of this model. Month fixed effects are included to account for the potential impact of general market conditions on returns, however.

The primary focus of this model is the two dummies, *Membership* and *Profitable*, and the interaction terms which incorporate them. *MemberProfitable* captures the variation of the membership effect for profitable members on the dependent variable relative to all other members. Adding the estimated number of friends a member has to that interaction then indicates the degree to which changes in the number of network connections for profitable traders influences the dependent variable, again relative to all other members.

The relative comparison of the two interaction terms is important in this analysis from two perspectives. First, to the extent that there might be some general observability effect at work from simply being a member, if profitable traders are indeed more subject to an audience influence then it would be expected to show up in the *MemberProfitable* coefficient. Second, to the extent that having more friends increases observation and thereby increases the theorized audience effect, the *MemberProfitableFriends* coefficient would be expected to capture it.

Table 6.2 provides a correlation analysis of the primary variables included in these regressions, and those to follow. As was observed when looking at Table 5.8 from last chapter, *Excess Return* does not have a strong correlation to any of the other variables. The strongest correlations are between

Spread and *EUR or USD* and *Non-Major*. This is to be expected as the more liquid currencies have narrower (less negative) spreads. Similarly, the high correlation between *Membership* and *Friends* is as expected. Aside from that, there are no strong correlations elsewhere.

Table 6.3 presents the results from Equation 6.1.The two takeaways from Table 6.3 are that profitable traders tend to operate in somewhat more illiquid and volatile currencies. Also the more friends a network member has, the more they tend toward lower volatility, higher liquidity currency pairs. In neither case are the significance levels high, however. The friends observation may indicate a broad audience effect of some kind. The *MemberProfitableFriends* term is insignificant, however. This indicates that profitable traders are no more or less impacted than any other members. Membership generally has no impact. Leverage is positive and significant in all tests, though that is not necessarily surprising. It likely simply reflects a normalizing of per trade risk which would result in higher leverage use when trading lower volatility exchange rates.[89]

To examine the question of instrument selection more narrowly, and provide a secondary test of both Hypothesis 1, the model in Equation 6.1 can be adapted to examine the currency selection question from two additional perspectives.

$$\begin{aligned} EURorUSD_{i,\mathrm{t}} = {} & \alpha + \beta_1 Leverage_{i,\mathrm{t}} + \beta_2 Membership_{i,\mathrm{t}} \\ & + \beta_3 Profitable_i + \beta_4 MemberProfitable_{i,\mathrm{t}} \\ & + \beta_5 Friends_{i,\mathrm{t}} + \beta_6 MemberProfitableFriends_{i,\mathrm{t}} + u_{i,\mathrm{t}} \end{aligned} \quad (6.2)$$

$$\begin{aligned} NonMajor_{i,\mathrm{t}} = {} & \alpha + \beta_1 Leverage_{i,\mathrm{t}} + \beta_2 Membership_{i,\mathrm{t}} \\ & + \beta_3 Profitable_i + \beta_4 MemberProfitable_{i,\mathrm{t}} \\ & + \beta_5 Friends_{i,\mathrm{t}} + \beta_6 MemberProfitableFriends_{i,\mathrm{t}} + u_{i,\mathrm{t}} \end{aligned} \quad (6.3)$$

Where

$EURorUSD_{i,t}$ is a dummy variable indicating whether position *t* executed by Trader *i* features a currency pair which includes the euro and/or the US dollar.

[89] For example, say a trader wants to risk 1% of their capital on a given trade. Given that the trader has defined how many "points" they are willing to risk (where they will place their stop loss exit order), it is a simple question of calculating position size (and thereby leverage) to match the desired 1% risk with the exposure defined by the stop loss. If a market is more volatile, it implies the need for a larger distance between the entry point and the stop loss. That means a higher nominal risk, which is then accounted for by reducing position size.

$NonMajor_{i,t}$ is a dummy variable indicating whether position *t* executed by Trader *i* features a currency pair which includes no more than one of the major currencies (USD, EUR, GBP, JPY, AUD, CHF, or CAD).

Remaining variables as previously defined.

With these two models a closer examination is made of the fraction of trades done in certain types of currency pairs. In Equation 6.2 the focus is on the proportion of trades done in the two most active currencies, while Equation 6.3 turns attention on those currency pairs which are among the least actively traded. It should be noted that there is overlap between the two groups. One can trade a USD or EUR pair which is considered a non-major. An example of this would be USD/MXN, which is the US dollar exchange rate against the Mexican peso. A trade in this currency pair would count in both categories.

Tables 6.4 and 6.5 present the regression results, staying with the member-clustered OLS method and robust standard errors.[90] It is noteworthy that in neither case do the profitable traders show any different currency pair trade allocation than everyone else (at least in general terms) as indicated by the failure of the *Profitable* dummy to have any significance. On the face of it, these two sets of regressions might seem to provide support for the friend effect on influencing members toward more conservative currency pair selections noted above. The *Friends* variable coefficient is positive and significant for *EURorUSD* (0.016), suggesting a friend-motivated shift to greater trading in those currencies, while it is negative and significant for *NonMajor* (-0.010), indicating a shift away from the more volatile and illiquid currencies. This may only be picking up the fact that more people trade in the EUR and USD and they may be friending each other on that basis, however.

In the case of *NonMajor* there is a contrary indication for the profitable group. The *MemberProfitableFriends* interaction term is positive and significant (0.022), suggesting more friends actually encourages the better market timers in the network toward the more exotic currency pairs. The significance is not strong, however. The bottom line is that based on these findings there is little or

[90] I acknowledge there are other methods which could be argued are better for the analysis of non-continuous dependent variables (e.g. probit/logit). However, it is unlikely they would produce a significantly different result.

no support for Hypothesis 1 that more sophisticated traders change traded instruments as their level of observation increases.

6.4.2. Does observation encourage more rapid exits?

The planning phase of trading cannot be observed after the fact, but it is at least possible to get some idea of what happened in the execution phase. Specifically, the timing of trade exits may be analysed to see if there is any change in pattern. While the size of any given gain or loss is likely heavily reliant on trade entry decisions (combined with subsequent market action), which are unobservable, it is possible to examine the holding period of positions for potential evidence of an audience influence. Hypothesis 2 proposes that winning trades would be more quickly or slowly exited, while Hypothesis 3 makes a similar suggestion about losing trades. To test these hypotheses, two models may be utilized:

$$\begin{aligned} WinHold_{i,t} = \; & \alpha + \beta_1 Leverage_{i,\mathrm{t}} + \beta_2 Membership_{i,\mathrm{t}} + \beta_3 Profitable_i \\ & + \beta_4 MemberProfitable_{i,\mathrm{t}} + \beta_5 Friends_{i,\mathrm{t}} \\ & + \beta_6 MemberProfitableFriends_{i,\mathrm{t}} + u_{i,\mathrm{t}} \end{aligned} \tag{6.4}$$

$$\begin{aligned} LossHold_{i,t} = \; & \alpha + \beta_1 Leverage_{i,\mathrm{t}} + \beta_2 Membership_{i,\mathrm{t}} \\ & + \beta_3 Profitable_i + \beta_4 MemberProfitable_{i,\mathrm{t}} \\ & + \beta_5 Friends_{i,\mathrm{t}} + \beta_6 MemberProfitableFriends_{i,\mathrm{t}} + u_{i,\mathrm{t}} \end{aligned} \tag{6.5}$$

Where

$WinHold_{i,t}$ is the log of the duration of position *t* executed by Trader *i* if that trade is a winner.

$LossHold_{i,t}$ is the log of the duration of position *t* executed by Trader *i* if that trade is a loser

Remaining variables as previously defined.

Again, leverage is included in the model to capture the position size decision, while currency pair fixed effects are used to account for instrument selection decisions. The results of these two sets of member-clustered OLS regression can be found in Tables 6.6 and 6.7 respectively. The primary takeaway of the findings is that the degree of observation – at least as measured by friend connections – does not meaningfully impact on trade holding period. It does not matter whether one talks about winning or losing trades. Neither of the two tables shows the coefficient of *Friends* or

MemberProfitableFriends as being significant. As such, neither Hypothesis 2 that sophisticated traders would be increasingly influenced to change their winning trade holding lengths as they are more observed nor Hypothesis 3 that sophisticated traders would be increasingly influenced to change their losing trade holding lengths as they are more observed is supported.

Nevertheless, there are some worthwhile observations. The first is that the profitable group tends to hold both winning and losing trades longer than do others. This is perhaps to be expected given that they were selected on the basis of mean excess trade return. Longer holding periods tend to mean capturing greater volatility. The other observation is that the profitable traders do appear to be motivated toward faster exits of winning trades as members of the network. This does not show in the *MemberProfitable* coefficient until adding in *Friends*, and especially the *MemberProfitableFriends* interaction. The coefficient for the latter, while not significant, is positive. The implication there is that increased observability may actually counter a tendency to exit winning trades more quickly. As such, it is possible that there are conflicting influences toward greater loss aversion and an increased desire to appear more savvy by fighting against the influences of the disposition effect.

6.4.3. Does observability drive overconfidence?

The fourth hypothesis of this chapter speaks to the position size decision a trader makes before entering a new position, specifically from the point of view of trade volume relative to the size of one's account - leverage. The theorization is that the larger the audience and the dissemination of outgoing information, the greater the overconfidence, leading to an increase in leverage use. The following model can be applied to test Hypothesis 4:

$$\begin{aligned} Leverage_{i,t} = \alpha + \beta_1 Membership_{i,t} + \beta_2 Profitable_i \\ + \beta_3 MemberProfitable_{i,t} + \beta_4 Friends_{i,t} \\ + \beta_5 MemberProfitableFriends_{i,t} + u_{i,t} \end{aligned} \tag{6.6}$$

It will be observed that *Friends* is the only random variable included in this model. While it would be possible to include spread as reflective of the instrument decision being made, a currency pair fixed effect is used instead to provide more precision (in theory, multiple currency pairs could have the same spread return value at a given point in time).

The results of running the member-clustered OLS regressions for this model can be found in Table 6.8. The indications are interesting. Firstly, the *Profitable* dummy is negative and significant across the board (about -0.74), which suggests that these traders tend to use less leverage on average than do others. This is no real surprise given the findings from Chapter 4 that more sophisticated traders tend to trade at lower leverage levels (though the significance is not overly strong). More directly related to the research question at hand, the *MemberProfitableFriends* interaction term's coefficient is positive with very high significance and an economically meaningful coefficient (0.532). This is support of the Hypothesis 4 idea that the greater one's audience, the greater one's overconfidence.

Importantly, members of the network under consideration here could not observe each other's level of leverage use – at least not directly.[91] That means leverage use was not something available for use as the basis of identifying others to connect with in the network in the same way as something like currencies traded. Additionally, the profitable traders in this case were identified on the basis of their market timing ability, not their monthly returns, which would have been influenced by leverage.[92] As a result, there is little risk of a reverse causality issue in these results – that higher friend counts were a function of greater leverage use rather than greater leverage use being a function of a higher number of friends.

It is worth noting that in the case of leverage there is no member level effect – either generally or with respect to the profitable members. The implication is that simply the fact of being observed is not sufficient to influence overconfidence. It is specifically the size of a trader's audience which drives them toward greater leverage use. Arguably, this makes the support for Hypothesis 4 even stronger.

6.4.4. Does an audience alter market timing strategy?

The question of instrument selection and position sizing with regards to trade entry have been addressed. So too has the question of whether there is

[91] The more ambitious network members might have been able to back out leverage use from the net returns they could observe. This would only be reasonably possible in the case of traders who never had overlapping positions or multiple trades in a given time period, however. That rules out the vast majority of the traders in this study.
[92] There is less than a 40% overlap between the top quartile of traders in terms of market timing and the top quartile in terms of mean monthly return (both on the basis of the pre-membership period).

an influence on trade disposition. It is now left to consider the final outcome of trades as a probable indication of impression management on performance. Hypothesis 5 proposes that observation encourages a trader to alter some aspect of their decision-making process with respect to market timing. This may be something as simple as becoming more hesitant to pull the trigger, or it could be as significant as shifting to a different analytic approach altogether. There is no way of knowing without direct observation what is really happening. That just leaves the analysis of outcomes to ascertain whether there is some change in behaviour at work.

Since the group being examined in this analysis is one which has demonstrated strong market timing performance, it makes sense to gauge whether they change behaviour by using a metric directly related to that ability. That is unleveraged trade excess return. This is a superior measure to simple trade return (the mean version of which was used in Chapter 4) because it removes other variables unrelated to the entry and exit decision-making process from the equation. With that in mind, the following model is proposed to test Hypothesis 5:

$$\begin{aligned} ExcessReturn_{i,t} &= \alpha + \beta_1 Leverage_{i,\mathrm{t}} + \beta_2 Membership_{i,\mathrm{t}} \\ &+ \beta_3 Profitable_i + \beta_4 MemberProfitable_{i,\mathrm{t}} \\ &+ \beta_5 Friends_{i,\mathrm{t}} + \beta_6 MemberProfitableFriends_{i,\mathrm{t}} + u_{i,\mathrm{t}} \end{aligned} \tag{6.7}$$

Where

$ExcessReturn_{i,t}$ is the exchange rate change captured by position *t* executed by Trader *i* after accounting for the bid/ask spread.

Remaining variables as previously defined.

Although the use of excess return in this case, because it only incorporates the change in the exchange rate, removes the influence of position size on the value of the dependent variable, leverage has still been included in the model as a control. Similarly, the use of currency pair fixed effects is retained. Both serve to capture aspects of the trade decision-making process which go beyond the question of when to buy and sell.

Table 6.9 outlines the regressions results based on this model, again working on an OLS basis with clustering on member and robust standard errors.

As would be expected, the coefficient of the *Profitable* dummy is positive and significant across the board. Interestingly, the *Membership* dummy comes through as negative and significant up to the point where the *MemberProfitable* interaction term is introduced, after which the coefficient is no longer significant. That *MemberProfitable* is negative and strongly significant points to the how much of an adverse impact the traders in the profitable group experience once they become members of the network. Although *Friends* does not come through as significant, the *MemberProfitableFriends* interaction term is negative and significant (-0.00017), with only a small change in the coefficient value for *MemberProfitable*. This indicates that while there is a general membership effect on market timing performance, it is exacerbated as one's audience increases. This is evidence in support of Hypothesis 5 in terms of sophisticated traders experiencing increasingly lower excess returns the more they are observed. It would appear that observation does lead to some kind of change in the way these profitable traders plan and/or execute their trades.

One point of interest in the Table 6.9 results is that the coefficient for *Leverage* is not significant. This would seem to be contradictory to the findings of Chapter 4 where leverage is shown to be an influencing factor on average deleveraged trade returns, which are closely akin to the excess return values being examined here. Recall that the Chapter 4 results were based on monthly aggregates, however. My hypothesis is that overconfidence as indicated by leverage use is expressed at a higher time frame level than per trade. This fits with the findings from Section 6.4.3 in that changes in the size of one's audience are unlikely to happen at the trade-by-trade level, but rather in a higher time frame – especially in a high frequency trading environment.

Further, at the individual transaction level the leverage decision may be a function of the nominal risk the position is viewed as taking and how that relates to the risk the traders wishes to take relative to their account size. For example, if a trader decides to risk 2% of their capital on a position, then the amount of leverage applied is considerably different if the nominal risk of the trade is 10 points as opposed to 20 points. Thus, at the trade level leverage use is a function of a higher level decision (percent of capital risked) and the current trade operating parameters (where the trader places their stop loss order). If it is expected that traders do not change their per trade risk level from transaction to transaction, but only do so in broader spans of time, then overconfidence driven changes in leverage use is not necessarily challenged by the Table 6.9 results.

6.4.5. Robustness checks

The main decision-point consideration for this chapter not already addressed in the sections above or previously in Chapters involves the exclusion of the two high-friend members - neither of whom are in the profitable group. Including them in the analysis has mixed effects on the results (not presented). In the case of the spread analysis show in Table 6.3, the *Friends* coefficient is more negative and the significance is higher in both of the last two columns. This does not alter the main conclusion. For the EUR or USD results in Table 6.4 and the non-majors results from 6.5, the findings are basically unchanged. This also holds for the results for the winning and losing trade holding periods shown in Tables 6.6 and 6.7. In the case of the leverage results from Table 6.8, including the dropped members causes the *Friends* coefficient from the last two columns to become negative and significant, which in turn sees the coefficient for *MemberProfitableFriends* rise to about 0.68 (already highly significant). Finally, in the case of the Table 6.9 results focused on trade excess returns, the only influence is a slight drop in the significance of *MemberProfitableFriends* in the last column, but no real change in the coefficient of that interaction term or the *Friends* variable. Thus, where there is any impact, including the two high friend count members tends to strengthen the findings presented above.

It is noted in Section 6.3 that the excess return values used can be thought of in a similar way as the average deleveraged return value analysed in Chapter 4. Aside from the latter being a mean and the former an actual value for each transaction, the only difference between the two is that excess return has the spread component of the return removed (or more correctly, added back in). An alternate set of tests using a deleveraged return value – the exchange rate move captured inclusive of the spread – produces virtually identical results to those for excess return.

Because all the analysis in this chapter is done on a transaction basis, there is potential value in estimating a member's friend connections when each trade is executed. This is done on the same "earliest possible connection" basis as the monthly figures, but can be accomplished in two different ways. One is using only connections between active members (those who have done at least one trade in a network-connected account) while the other includes all members. It is the active member segment which is applied in Chapter 5 because non-active members do not transmit any information through the network via their trading. For consistency, that same group is used in this chapter. While focusing only on active members does make sense when considering an audience who is actually participatory, an argument can be made that one could be influenced by their total friend count. For that reason, it is worth considering trade level friend estimates from both perspectives.

Secondary analysis based on these two estimation methods produces little difference in results, however. In the case of the active-only tests the results are almost identical. When including the inactive members (which results in a significantly higher mean friend count, as would be expected), the results are similar enough not to change the primary conclusions. The one place where both sets of analysis do show a difference is in the case of Excess Return (Table 6.9). In both cases, the *MemberProfitableFriends* interaction term loses significance, though *MemberProfitable* is unaffected. This suggests a sensitivity to friend counts for that activity metric, but the fact that *MemberProfitable* remains negative and significant continues to suggest an audience effect, just one based on existence rather than on size.

Of additional note, as in the prior chapters, alternative panel regression analysis generally provides more significant results than those presented herein. The OLS alternative results are presented as representing the more conservative approach.

6.5. Conclusion & Further Discussion

The purpose of this chapter is to examine the question of whether being exposed to observation by one’s peers (broadly speaking) influences an investor’s behaviour. The primary evidence presented for just such an effect comes from Tables 6.8 and 6.9 where a link is made between a higher number of friends in a social network (higher observability, larger audience, greater judgement influencing communication) and both increased leverage use and increasingly impaired market timing performance. In Chapter 4 a connection between increased leverage use and a decrease in trade excess returns is developed, suggestive of the idea that not only does increased overconfidence hurt returns from the perspective of larger transaction costs, it also results in diminished market-timing effectiveness. The findings of this chapter again highlight the relationship between overconfidence and the making of worse trade decisions – or perhaps the shift toward a different, less effective, trading strategy, though that cannot be observed.

A natural reaction to seeing market timing performance reductions related to audience size is to consider the effect of an investor's followers copying their trading strategy. Presumably, this sort of activity would eventually degrade that strategy's performance. Certainly in the case of institutional investors this would be a concern, which is a factor in why they seek to mask their activity. As is discussed in Chapter 2, in the case of retail forex trading this is not a meaningful consideration since retail volumes likely represent less than 5% of inter-bank market trading, however. The inter-bank market is where global exchange rates are set, so the retail market's impact is small. Going a step further, members of the social network in question may have had a few hundred friends at most, which would be a tiny fraction of market participants. In other words, even if every one of a member's friends is employing the same strategy, it would have no impact on exchange rates, and thus that can be ruled out as explaining the drop in trade excess returns.

In the case of instrument selection and trade disposition, the results are largely unsupportive of the developed hypotheses. That said, there are some considerations worth examining. The first is that there could be a general effect related to simply joining the network. To the extent that doing so means one's trading activity is visible to others in one fashion or another there could be a type of panopticon effect whereby a trader is impacted by the understanding that that they *could* be observed at any given time. As Johnson (2008) observes with regards to the type of information gathering happening in this kind of social network structure, "*Individuals would know that most of what they do can be observed and this could influence how they behave.*" There is evidence for this level of behavioural influence in Table 6.9 where trade excess returns are indicated as being negatively influenced by network membership well above and beyond any connection to friend count. The same can be said of the length of the holding period of winning trades as documented in Table 6.6. An interesting potential extension of this research would be to link observability with measures of emotional state at the time of trade entry per the findings of Lo et al. (2005) that the latter is important in the context of real-time decision-making.

Moving down to the level of degrees of observation, there is the question of a differentiation in observer effect based on personality types, as suggested by Grant and Dajee (2003) and Uziel (2007). Certain types of effects may be washed out by having traders of different characters reacting to being observed in opposing ways. For example, Table 6.8 shows a strong positive link between increased audience size and leverage use, though there is little in the way of support for an audience link to risk-seeking behaviour where currency or currency pair selection is concerned. It may be in the latter case that even if there is relatively little personality type variation within the group of profitable traders (111 members), it is enough to keep results from being significant. With a richer data set it should be possible to examine these questions at a more granular level.

From a broader perspective, it could be that there is a personality aspect to these who join a trading social network which is seen across all members – or at least a significantly large portion of them. The findings from Tables 6.3, 6.4, and 6.5 showing a friend influence on currency and currency pair selection seem to point in that direction. This is a self-selection issue with the data used in this study. A randomized study or the ability to otherwise compare network member traders with a control sample would be useful in addressing this issue.

It must be noted that since actual friend connection counts are not available for most of the sample period, and therefore estimates are used in their place, there is the potential for faulty estimates to have influenced the results. This is suggested in the robustness analysis from Section 6.4.5. Even if the estimates are close enough to reality as to not meaningfully influence the findings, there are still ways which the research could potentially be improved. The analysis herein assumes that all friend connections are of equal exposure and importance value. The reality of the situation, though, is that certain friends – or types of friends – may have much more meaning and influence on a member's behaviour than others, or drive a different type of behaviour, as per Seta and Seta (1995). The degree of actual observation, and of interaction, is also potentially relevant.

Additionally, there is the question of the directionality of the "friending" behaviour underlying the development of network connections. It is perhaps a reasonable assumption that it is lesser skilled traders seeking to connect with more skilled ones which drives connectivity. Certainly, expectations would support that sort of behaviour as something which could drive increased overconfidence, even without taking into account the theories around impression management. Unfortunately, the dataset employed herein lacks information with regards to which member of a friend pair is the initiating party. It would be of research interest to be able to ascertain whether that directionality plays a part in any or all of the influences examined in this chapter.

Potentially of most importance in this discussion is the question of what exactly traders would consider socially desirable or acceptable behaviour. What is the financial markets equivalent of the Munger and Harris (1989) hand washing? Some ideas are put forward here, but a more thorough examination of the subject is warranted. Further, it has to be considered that what is deemed desirable or acceptable may vary depending on the character of the investor in question and their relationship to their audience.

Table 6.1
Descriptive Statistics for Pre-Membership vs. Post-Entry Periods and Social Capital Measures for Social Network Traders

Sample of 443 retail foreign exchange traders for July 2008 to April 2013, including 488,661 round-turn transactions. Excess Return is the exchange rate move captured by a trade after accounting for the bid/ask spread. Leverage ratio of position size to account balance a trade. Duration is the holding period of a trade. Spread is the return equivalent of the bid/ask spread (always negative) for a given trade. EUR & USD is an indication of trades which include the euro and/or the US dollar in the transacted currency pair. Non-Major is an indication of trades in which the transacted currency pair does features no more than one of the major currencies (USD, EUR, GBP, JPY, AUD, CAD, CHF). (* p<0.10; ** p<0.05; *** p<0.01)

Panel A: All Members

	Non-Member: 198,356 Observations				Member: 290,305 Observations				
	Mean	**Std. Dev.**	**25%**	**75%**	**Mean**	**Std. Dev.**	**25%**	**75%**	**Change**
Excess Return	0.0228%	0.6808%	-0.0363%	0.1263%	-0.0089%	0.6830%	-0.0836%	0.1371%	-0.03167%***
Leverage (N:1)	5.30	17.72	0.40	3.98	3.67	12.87	0.22	2.59	-1.63***
Duration (Days)	1.58	12.26	0.01	0.35	1.67	12.01	0.02	0.53	0.087**
Spread (Bid/Ask return)	-0.0151%	0.0096%	-0.0185%	-0.0077%	-0.0144%	0.0094%	-0.0176%	-0.0077%	0.0008%***
EUR & USD	85.40%				89.27%				3.87%***
Non-Major	8.17%				6.11%				-2.06%***

Panel B: Profitable Members Only (111 traders)

	Non-Member: 21,790 Observations				Member: 43,516 Observations				
	Mean	**Std. Dev.**	**25%**	**75%**	**Mean**	**Std. Dev.**	**25%**	**75%**	**Change**
Excess Return	0.1926%	1.2438%	0.0124%	0.3438%	0.0160%	0.9524%	-0.1027%	0.2377%	-0.1766%***
Leverage (N:1)	2.09	7.02	0.18	1.60	1.91	6.10	0.10	1.58	-0.18***
Duration (Days)	5.46	22.90	0.06	2.33	2.90	11.64	0.06	1.53	-2.56***
Spread (Bid/Ask return)	-0.0172%	0.0116%	-0.0192%	-0.0123%	-0.0167%	0.0123%	-0.0192%	-0.0081%	0.0005%***
EUR & USD	84.30%				85.92%				1.62%***
Non-Major	9.70%				8.16%				-1.54%***

Table 6.2
Correlations of Study Variables

Sample of 443 retail foreign exchange traders for July 2008 to April 2013, including 488,661 round-turn transactions. Excess Return is the exchange rate move captured by a trade after accounting for the bid/ask spread. Leverage is the ratio of position size to account balance a trade. Duration is the holding period of a trade. Spread is the return equivalent of the bid/ask spread (always negative) for a given trade. EUR & USD is an indication of trades which include the euro and/or the US dollar in the transacted currency pair. Non-Major is an indication of trades in which the transacted currency pair does features no more than one of the major currencies (USD, EUR, GBP, JPY, AUD, CAD, CHF). Friends is the log of 1 plus the estimated number of friend connections for the trader in the month during which a trade takes place. Membership is a dummy set to 1 for months in which an individual is part of the network. Profitable is a dummy set to 1 for individuals whose mean excess trade returns pre-membership were in the top quartile. Excess Return, Leverage, and Duration winsorized at 1% and 99%

	Excess Return	**Leverage**	**Duration**	**Spread**	**EUR or USD**	**Non-Major**	**Friends**	**Membership**	**Profitable**
Excess Return	1.00								
Leverage	0.02	1.00							
	(0.00)								
Duration	-0.08	-0.18	1.00						
	(0.00)	(0.00)							
Spread	-0.05	0.08	-0.18	1.00					
	(0.00)	(0.00)	(0.00)						
EUR or USD	-0.02	0.04	-0.11	0.58	1.00				
	(0.00)	(0.00)	(0.00)	(0.00)					
Non-Major	0.03	0.00	0.06	-0.63	-0.30	1.00			
	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)				
Friends	-0.01	-0.07	-0.05	0.07	0.08	-0.07	1.00		
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)			
Membership	-0.03	-0.13	0.07	0.04	0.06	-0.04	0.44	1.00	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		
Profitable	0.06	-0.16	0.21	-0.09	-0.03	0.03	-0.11	0.06	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

Table 6.3

Implications of Observation on Currency Pair Selection for the Best Market Timers Amongst Members of a Retail Forex Trader Social Network, with Month Fixed Effects

$$\boldsymbol{Spread_{i,\mathrm{t}} = \alpha + \beta_1 Leverage_{i,\mathrm{t}} + \beta_2 Membership_{i,\mathrm{t}} + \beta_3 Profitable_i + \beta_4 MemberProfitable_{i,\mathrm{t}} + \beta_5 Friends_{i,\mathrm{t}} + \beta_6 MemberProfitableFriends_{i,\mathrm{t}} + u_{i,\mathrm{t}}}$$

Sample of 443 retail foreign exchange traders for July 2008 to April 2013, including 488,661 round-turn transactions. Leverage is the log of the ratio of position size to account balance a trade, winsorized at 1% and 99%. Membership is a dummy set to 1 for months in which an individual is part of the network. Profitable is a dummy set to 1 for individuals whose mean excess trade returns pre-membership were in the top quartile. Member-Profitable is an interaction term equal to Membership x Profitable. Friends is the log of 1 plus the estimated number of friend connections for the trader in the month during which a trade takes place. Member-Profitable-Friends is an interaction terms calculated as Membership x Profitable x Friends. Results are from an Ordinary Least Squares (OLS) regression clustered on member with robust standard errors using month fixed effects, and are expressed in terms of the return of the bid/ask spread (always negative). Standard errors indicated below the coefficients. (* p<0.10; ** p<0.05; *** p<0.01)

Test	**Membership**	**Profitable**	**Member-Profitable**	**Friends**	**Member-Profitable-Friends**
Intercept	-0.000142***	-0.000140***	-0.000140***	-0.000140***	-0.000140***
	(0.000017)	(0.000016)	(0.000016)	(0.000016)	(0.000016)
Leverage	0.000005***	0.000005***	0.000005***	0.000005***	0.000005***
	(0.000002)	(0.000002)	(0.000002)	(0.000002)	(0.000002)
Membership	0.000001	0.000002	0.000001	-0.000005	-0.000006
	(0.000008)	(0.000008)	(0.000008)	(0.000009)	(0.000009)
Profitable		-0.000022**	-0.000026*	-0.000026*	-0.000026*
		(0.000010)	(0.000013)	(0.000013)	(0.000014)
Member-Profitable			0.000006	0.000010	0.000014
			(0.000014)	(0.000014)	(0.000016)
Friends				0.000004*	0.000004*
				(0.000002)	(0.000002)
Member-Profitable-Friends					-0.000005
					(0.000006)
Adjusted R^2	6.40%	7.00%	7.01%	7.37%	7.40%

Table 6.4

Implications of Observation on EUR and USD Trading Frequency for the Best Market Timers Amongst Members of a Retail Forex Trader Social Network, with Month Fixed Effects

$$\boldsymbol{EURorUSD_{i,t} = \alpha + \beta_1 Leverage_{i,t} + \beta_2 Membership_{i,t} + \beta_3 Profitable_i + \beta_4 MemberProfitable_{i,t} + \beta_5 Friends_{i,t} + \beta_6 MemberProfitableFriends_{i,t} + u_{i,t}}$$

Sample of 443 retail foreign exchange traders for July 2008 to April 2013, including 488,661 round-turn transactions. Leverage is the log of the ratio of position size to account balance a trade, winsorized at 1% and 99%. Membership is a dummy set to 1 for months in which an individual is part of the network. Profitable is a dummy set to 1 for individuals whose mean excess trade returns pre-membership were in the top quartile. Member-Profitable is an interaction term equal to Membership x Profitable. Friends is the log of 1 plus the estimated number of friend connections for the trader in the month during which a trade takes place. Member-Profitable-Friends is an interaction terms calculated as Membership x Profitable x Friends. Results are from an Ordinary Least Squares (OLS) regression clustered on member with robust standard errors using month fixed effects, and are expressed in terms of the fraction of trades featuring the euro and/or US dollar. Standard errors indicated below the coefficients. (* p<0.10; ** p<0.05; *** p<0.01)

Test	**Membership**	**Profitable**	**Member-Profitable**	**Friends**	**Member-Profitable-Friends**
Intercept	0.899***	0.901***	0.901***	0.901***	0.900***
	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)
Leverage	0.013**	0.012**	0.012**	0.013**	0.013**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Membership	0.009	0.010	0.009	-0.017	-0.019
	(0.021)	(0.021)	(0.023)	(0.025)	(0.026)
Profitable		-0.019	-0.024	-0.024	-0.024
		(0.033)	(0.044)	(0.044)	(0.044)
Member-Profitable			0.008	0.024	0.039
			(0.046)	(0.046)	(0.051)
Friends				0.016***	0.017***
				(0.006)	(0.006)
Member-Profitable-Friends					-0.023
					(0.020)
Adjusted R^2	6.74%	6.77%	6.77%	7.22%	7.26%

Table 6.5

Implications of Observation on Non-Major Currency Pair Selection for the Best Market Timers Amongst Members of a Retail Forex Trader Social Network, with Month Fixed Effects

$$\boldsymbol{NonMajor_{i,t} = \alpha + \beta_1 Leverage_{i,t} + \beta_2 Membership_{i,t} + \beta_3 Profitable_i + \beta_4 MemberProfitable_{i,t} + \beta_5 Friends_{i,t} + \beta_6 MemberProfitableFriends_{i,t} + u_{i,t}}$$

Sample of 443 retail foreign exchange traders for July 2008 to April 2013, including 488,661 round-turn transactions. Leverage is the log of the ratio of position size to account balance a trade, winsorized at 1% and 99%. Membership is a dummy set to 1 for months in which an individual is part of the network. Profitable is a dummy set to 1 for individuals whose mean excess trade returns pre-membership were in the top quartile. Member-Profitable is an interaction term equal to Membership x Profitable. Friends is the log of 1 plus the estimated number of friend connections for the trader in the month during which a trade takes place. Member-Profitable-Friends is an interaction terms calculated as Membership x Profitable x Friends. Results are from an Ordinary Least Squares (OLS) regression clustered on member with robust standard errors using month fixed effects, and are expressed in terms of the fraction of trades in which no more than one of the major currencies features (USD, EUR, GBP, JPY, AUD, CAD, CHF). Standard errors indicated below the coefficients. (* p<0.10; ** p<0.05; *** p<0.01)

Test	**Membership**	**Profitable**	**Member-Profitable**	**Friends**	**Member-Profitable-Friends**
Intercept	0.091*	0.088*	0.088*	0.088**	0.088**
	(0.047)	(0.046)	(0.045)	(0.045)	(0.045)
Leverage	-0.001	0.000	0.000	0.000	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Membership	-0.011	-0.012	-0.009	0.006	0.008
	(0.014)	(0.014)	(0.014)	(0.016)	(0.016)
Profitable		0.022	0.035	0.035	0.034
		(0.020)	(0.033)	(0.033)	(0.033)
Member-Profitable			-0.019	-0.029	-0.044
			(0.031)	(0.032)	(0.035)
Friends				-0.010**	-0.011**
				(0.004)	(0.005)
Member-Profitable-Friends					0.022*
					(0.013)
Adjusted R^2	8.43%	8.51%	8.53%	8.81%	8.88%

Table 6.6

Implications of Observation on Winning Trade Holding Length for the Best Market Timers Amongst Members of a Retail Forex Trader Social Network, with Month and Currency Pair Fixed Effects

$$WinHold_{i,t} = \alpha + \beta_1 Leverage_{i,t} + \beta_2 Membership_{i,t} + \beta_3 Profitable_i + \beta_4 MemberProfitable_{i,t} + \beta_5 Friends_{i,t} + \beta_6 MemberProfitableFriends_{i,t} + u_{i,t}$$

Sample of 443 retail foreign exchange traders for July 2008 to April 2013, including 312,729 round-turn transactions. Leverage is the log of the ratio of position size to account balance a trade, winsorized at 1% and 99%. Membership is a dummy set to 1 for months in which an individual is part of the network. Profitable is a dummy set to 1 for individuals whose mean excess trade returns pre-membership were in the top quartile. Member-Profitable is an interaction term equal to Membership x Profitable. Friends is the log of 1 plus the estimated number of friend connections for the trader in the month during which a trade takes place. Member-Profitable-Friends is an interaction terms calculated as Membership x Profitable x Friends. Results are from an Ordinary Least Squares (OLS) regression clustered on member with robust standard errors using month and currency pair fixed effects, and are expressed in terms of the log of the duration of winning trades (winsorized at 1% and 99%). Standard errors indicated below the coefficients. (* p<0.10; ** p<0.05; *** p<0.01)

Test	**Membership**	**Profitable**	**Member-Profitable**	**Friends**	**Member-Profitable-Friends**
Intercept	-1.238**	-1.356**	-1.375**	-1.344**	-1.331**
	(0.581)	(0.546)	(0.540)	(0.551)	(0.552)
Leverage	-0.107***	-0.072**	-0.073**	-0.077**	-0.080**
	(0.040)	(0.036)	(0.036)	(0.038)	(0.038)
Membership	0.112	0.082	0.157	0.324*	0.342*
	(0.187)	(0.172)	(0.190)	(0.184)	(0.186)
Profitable		1.305***	1.631***	1.633***	1.630***
		(0.215)	(0.340)	(0.339)	(0.339)
Member-Profitable			-0.518	-0.632*	-0.760**
			(0.351)	(0.349)	(0.364)
Friends				-0.100	-0.110
				(0.068)	(0.071)
Member-Profitable-Friends					0.200
					(0.137)
Adjusted R^2	11.92%	15.10%	15.22%	15.53%	15.59%

Table 6.7
Implications of Observation on Losing Trade Holding Length for the Best Market Timers Amongst Members of a Retail Forex Trader Social Network, with Month and Currency Pair Fixed Effects

$$\boldsymbol{LossHold_{i,t} = \alpha + \beta_1 Leverage_{i,t} + \beta_2 Membership_{i,t} + \beta_3 Profitable_i + \beta_4 MemberProfitable_{i,t} + \beta_5 Friends_{i,t} + \beta_6 MemberProfitableFriends_{i,t} + u_{i,t}}$$

Sample of 443 retail foreign exchange traders for July 2008 to April 2013, including 175,685 round-turn transactions. Leverage is the log of the ratio of position size to account balance a trade, winsorized at 1% and 99%. Membership is a dummy set to 1 for months in which an individual is part of the network. Profitable is a dummy set to 1 for individuals whose mean excess trade returns pre-membership were in the top quartile. Member-Profitable is an interaction term equal to Membership x Profitable. Friends is the log of 1 plus the estimated number of friend connections for the trader in the month during which a trade takes place. Member-Profitable-Friends is an interaction terms calculated as Membership x Profitable x Friends. Results are from an Ordinary Least Squares (OLS) regression clustered on member with robust standard errors using month and currency pair fixed effects, and are expressed in terms of the log of the duration of losing trades (winsorized at 1% and 99%). Standard errors indicated below the coefficients. (* p<0.10; ** p<0.05; *** p<0.01)

Test	**Membership**	**Profitable**	**Member-Profitable**	**Friends**	**Member-Profitable-Friends**
Intercept	-1.567**	-1.572**	-1.577**	-1.609**	-1.611**
	(0.759)	(0.733)	(0.729)	(0.740)	(0.742)
Leverage	-0.307***	-0.287***	-0.286***	-0.293***	-0.295***
	(0.040)	(0.043)	(0.042)	(0.039)	(0.039)
Membership	-0.102	-0.138	-0.114	0.114	0.127
	(0.214)	(0.213)	(0.232)	(0.222)	(0.225)
Profitable		0.999***	1.157***	1.145***	1.141***
		(0.204)	(0.250)	(0.250)	(0.249)
Member-Profitable			-0.224	-0.341	-0.459
			(0.304)	(0.291)	(0.305)
Friends				-0.160	-0.169
				(0.115)	(0.120)
Member-Profitable-Friends					0.158
					(0.200)
Adjusted R^2	16.96%	18.28%	18.30%	18.96%	18.99%

Table 6.8

Implications of Observation on Leverage Use for the Best Market Timers Amongst Members of a Retail Forex Trader Social Network, with Month and Currency Pair Fixed Effects

$$\boldsymbol{Leverage_{i,t} = \alpha + \beta_1 Membership_{i,t} + \beta_2 Profitable_i + \beta_3 MemberProfitable_{i,t} + \beta_4 Friends_{i,t} + \beta_5 MemberProfitableFriends_{i,t} + u_{i,t}}$$

Sample of 443 retail foreign exchange traders for July 2008 to April 2013, including 488,661 round-turn transactions. Membership is a dummy set to 1 for months in which an individual is part of the network. Profitable is a dummy set to 1 for individuals whose mean excess trade returns pre-membership were in the top quartile. Member-Profitable is an interaction term equal to Membership x Profitable. Friends is the log of 1 plus the estimated number of friend connections for the trader in the month during which a trade takes place. Member-Profitable-Friends is an interaction terms calculated as Membership x Profitable x Friends. Results are from an Ordinary Least Squares (OLS) regression clustered on member with robust standard errors using month and currency pair fixed effects, and are expressed in terms of the log of the ratio of position size to account balance for the trade, and winsorized at 1% and 99%. Standard errors indicated below the coefficients.
(* p<0.10; ** p<0.05; *** p<0.01)

Test	**Membership**	**Profitable**	**Member-Profitable**	**Friends**	**Member-Profitable-Friends**
Intercept	-0.028	0.009	0.011	0.016	0.035
	(0.575)	(0.581)	(0.582)	(0.576)	(0.576)
Membership	-0.206	-0.183	-0.188	-0.094	-0.048
	(0.209)	(0.210)	(0.224)	(0.203)	(0.204)
Profitable		-0.721**	-0.745*	-0.744*	-0.748*
		(0.293)	(0.419)	(0.419)	(0.419)
Member-Profitable			0.037	-0.022	-0.380
			(0.455)	(0.453)	(0.460)
Friends				-0.060	-0.087
				(0.080)	(0.080)
Member-Profitable-Friends					0.532***
					(0.157)
Adjusted R^2	12.77%	14.33%	14.33%	14.51%	15.22%

Table 6.9

Implications of Observation on Trade Excess Returns for the Best Market Timers Amongst Members of a Retail Forex Trader Social Network, with Month and Currency Pair Fixed Effects

$$\begin{aligned}\boldsymbol{ExcessReturn_{i,t}} \\ = \boldsymbol{\alpha} + \boldsymbol{\beta_1 Leverage_{i,t}} + \boldsymbol{\beta_2 Membership_{i,t}} + \boldsymbol{\beta_3 Profitable_i} + \boldsymbol{\beta_4 MemberProfitable_{i,t}} + \boldsymbol{\beta_5 Friends_{i,t}} \\ + \boldsymbol{\beta_6 MemberProfitableFriends_{i,t}} + \boldsymbol{u_{i,t}}\end{aligned}$$

Sample of 443 retail foreign exchange traders for July 2008 to April 2013, including 488,661 round-turn transactions. Leverage is the log of the ratio of position size to account balance a trade, winsorized at 1% and 99%. Membership is a dummy set to 1 for months in which an individual is part of the network. Profitable is a dummy set to 1 for individuals whose mean excess trade returns pre-membership were in the top quartile. Member-Profitable is an interaction term equal to Membership x Profitable. Friends is the log of 1 plus the estimated number of friend connections for the trader in the month during which a trade takes place. Member-Profitable-Friends is an interaction terms calculated as Membership x Profitable x Friends. Results are from an Ordinary Least Squares (OLS) regression clustered on member with robust standard errors using month and currency pair fixed effects, and are expressed in terms of the exchange rate move captured by trades after accounting for the bid/ask spread, and winsorized at 1% and 99%. Standard errors indicated below the coefficients. (* p<0.10; ** p<0.05; *** p<0.01)

Test	**Membership**	**Profitable**	**Member-Profitable**	**Friends**	**Member-Profitable-Friends**
Intercept	0.00010	0.00006	0.00003	0.00002	0.00002
	(0.00026)	(0.00026)	(0.00026)	(0.00024)	(0.00024)
Leverage	0.00005	0.00007	0.00007	0.00007	0.00007
	(0.00008)	(0.00008)	(0.00008)	(0.00008)	(0.00008)
Membership	-0.00021**	-0.00023**	-0.00009	-0.00018	-0.00019
	(0.00009)	(0.00009)	(0.00010)	(0.00013)	(0.00013)
Profitable		0.00078***	0.00144***	0.00144***	0.00144***
		(0.00018)	(0.00023)	(0.00023)	(0.00023)
Member-Profitable			-0.00101***	-0.00096***	-0.00084***
			(0.00028)	(0.00029)	(0.00031)
Friends				0.00005	0.00006
				(0.00004)	(0.00004)
Member-Profitable-Friends					-0.00017**
					(0.00009)
Adjusted R^2	1.04%	1.39%	1.53%	1.55%	1.57%

Chapter 7: Conclusion

7.1. General

Broadly speaking, this thesis expands the financial literature in four main areas. First, it extends the analysis of traders and investors in the high frequency environment by employing transactional and performance data from retail foreign exchange traders. Second, it expands the research in to the foreign exchange arena which has thus far received limited attention despite it being the single largest financial market in the world. Third, it extends the work being done with respect to social networks in finance, particularly online networks, by incorporating a dataset from an online network of retail traders. Fourth, it expands the literature with respect to the impact of observation and impression management on investor behaviour and performance. Chapter 2 draws a link between high frequency trading and foreign exchange by describing the retail forex market structure, mechanics, and participants. Chapter 3 then goes on to describe the dataset used in this thesis which connects high frequency individual forex traders with social network participation. This is then used in the research chapters to examine questions of overconfidence and social influences on traders.

In Chapter 4 the subject of investor overconfidence is approached from a new angle. The use of leverage is proposed as a key indicator of the presence of overconfidence in the decision-making process, one which is hypothesized to offer more precise information than either the turnover or trade frequency metrics previously used in the literature. The analysis of leverage use among retail foreign exchanges traders, which are among the most active users of leverage in the financial markets, supports the hypothesis in two ways. First, increased leverage is demonstrated to be negatively associated with returns in the same way turnover is in the extant literature. Second, increased leverage use is associated with a diminished quality of trade decision-making in terms of the exchange rate moves being captured by the traders studied. These results are supported in the evaluation of differences in experience and level of sophistication with respect to expectations of their influence on investor overconfidence. The findings of Chapters 5 and 6 go on to further underline both the influence of leverage on performance and the link it has to the quality of the trades made by market participants. This expands the financial literature in terms of both putting leverage use under specific scrutiny and bringing overconfidence analysis in to the realm of high frequency trading where different considerations may be at work on behaviour than in traditional investment time frames.

Chapter 5 turns the focus on trader and investor social networks with a specific focus on the information transmission they potentially generate and the social impact the interactions involving the receipt of that transmission can have. The suggestion is made that networks of retail traders in “small” markets likely do not involve the transmission of meaningful amounts of private fundamental information, but that members may yet benefit from the exchange of information of a non-fundamental nature. The evaluation of retail foreign exchange traders in an online social network is made to determine whether any information benefit is in fact to be gained from participation when considering the level and degree of interaction a member has (at least potentially) with others and how they were positioned in the network.

The findings support the idea that at least some amount of useful information is transmitted through the network, but that those gains are offset by some kind of most likely social influence leading to markedly impaired returns. Those demonstrating a large information benefit are network members with the poorest pre-registration track record, which suggests the influence of endogenous information of an educational nature. More sophisticated members appear to experience no information benefit, which supports the hypothesis of a lack of meaningful non-public fundamental information transmission between members. Further, these sophisticated members appear to suffer a negative social effect from network membership resulting in significantly lower monthly returns. The existing literature with regards to the potential side effects of investor engagement does not offer sufficient explanation for these findings.

Trader social networks remain the theme on Chapter 6, but with the focus shifting from information receipt from others to information transmission. Of primary interest is the potential impact on investors of their activity and performance being observed by others based on concepts developed broadly in the psychology literature. The general hypothesis tested is that an increase in the degree to which one is observed, or believes themselves to be observed, leads to a stronger motive to shape one’s activity in the markets toward what is expected or to demonstrate savvy. The major findings are meaningful. Increased audience size is seen to be associated with greater overconfidence, as measured by leverage. At the same time, increased visibility in the form of a larger number of friends is linked to reduced excess trade returns. That combination of results both supports the hypothesis that audience size influences investor behaviour and performance, while also affirming the link between overconfidence and impaired market timing performance observed in Chapter 4. In the areas of instrument selection and potential disposition effects there are no conclusive findings of note, but a closer examination on the basis of trader heterogeneity is suggested. Further, there are some broader indications which may point to higher level observability effects which are introduced by the simple act of being able to be observed, regardless of audience size.

The findings of Chapters 5 and 6 extend the literature in financial social networks a number of ways. They include evaluating the actual intentional connectivity of individuals with others (as opposed to assuming connections on a theoretical basis) as well as in the analysis of the influence of network membership both from an information receipt and information sharing perspective. It also includes extending the behavioural finance literature in the areas of learning, experience and sophistication and their impact on trader and investor activity and performance. Additionally, these two chapters further develop the literature related to investor overconfidence and trade disposition.

7.2. Caveats

The dataset used for the analysis in this thesis provides a relatively unique opportunity to analyse the activity and performance of a thus far little-studied group of market participations. It does come with its share of issues and concerns, however. Top of the list is the manner in which it was constructed by combining a large number of data providers which did not have a uniform protocol for transmission. That created inconsistency in the data collected by the social network while at the same time there were acknowledged errors on the network side in handling some of that data. Every attempt is made to correct for potential data problems, but at a certain point one has to simply rely on the underlying systems and procedures generally being structured properly and producing accurate data.

On a related note, as much as the influence of non-trader initiated transactions (copy trades) is intended to be minimized to allow for the focus to remain on self-directed behaviour, they may still have had an influence. On an indirect basis, the performance of copied trades executed in a trader's account might have influenced that trader's decision-making where their own trading is concerned in terms of availability of marginable funds, the selection of exchange rates to trade, and the impact of profitability on risk taking. Any period where copied trades were executed in a trader's account were eliminated from consideration with respect to monthly returns, potentially meaning significant self-directed returns were excluded from the analysis. This would have impacted a relatively small number of traders, however, so the influence is not likely meaningful.

Data quality aside, there are two aspects to the dataset which are potentially biasing of the results produced by the analysis here. One is survivorship. The other is self-selection. Chapter 3 indicates the presence of survivorship in the way the number of active accounts gradually declined (Figure 3.2) even as those traders remaining active demonstrated even greater outperformance relative to the broader population (Table 3.7). The use of panel data regressions clustered on individual traders (and with trader fixed effects in places) does tend to minimize the concern about survivorship biasing the results. Even where it does not, the expectation would be that the results are slightly biased toward the better performers, which suggests that the general performance of traders is perhaps slightly worse than that seen here.

The self-selection issue is somewhat harder to overcome. It introduces a question into the social network analysis as to whether the changes in behaviour and performance observed are truly reflective of the influence of being part of the network or simply reflect the influence of a propensity on the part of the traders in question. In particular, the sharing of one's trading activity and returns with the public suggests a certain type of attitude. This is partly addressed by being able to control for whether one has opted to connect with others in the network, and of course in the analysis of returns and activity measures from before joining the network to after become a part. Still, to do a more thorough analysis it would be desirable to have a randomly developed trader social network.

7.3. Implications for Future Research

The findings presented in this thesis suggest some interesting follow-up research questions. Near the top of the list is in the area of leverage use, which thus far has received relatively little consideration in the literature, at least at the individual market participant level. The focus here is on a relatively uninfluential segment of the markets where price discovery is concerned, but leverage is a factor in trading in other, much more notable areas, including futures and equities. To the extent that a better understanding of what motivates changes in the leverage decision can be identified it would facilitate better risk management and improved investment/trading performance. The results featured in Chapters 5 and 6 provide a starting point in terms of offering a set of potential explanatory variables, but leave some open questions. One specific topic to consider is a possible link between leverage use and the disposition effect. If there is one, it has the potential to offer insight into market movements where leverage is readily employed.

Another takeaway from the analysis herein is that market participants should be evaluated in a much more segmented fashion than has thus far been the case. All three of the research chapters provide indications that traders with different levels of experience and/or sophistication show markedly different performance. Even more importantly where future research potential is concerned, they show variation in the drivers of that performance and of trading activity. Clearly, viewing market participants in a more heterogeneous fashion offers the opportunity to gain new insights into the way different dynamics in the market come together to influence prices and drive returns.

In the specific area of experience, questions abound as to things like source and time frames. The research here uses a fairly simple segmentation based on years in the market, but it provides little in the way of nuance. One question which immediately comes to mind is whether time is the appropriate indication of experience, or whether the volume of trading one has done is a better metric. Perhaps some combination of the two? Of course that also ties in with the question of education. How are traders learning and are those methods, such as social network participation, effective? The discussion regarding some of the foibles of retail forex traders had in Chapter 2 certainly questions the quality of whatever education these individuals may be getting.

Questions related to the influence of one's account balance are also worth considering here. Sophistication indication aside, it is very interesting in particular to observe the influence a trader's capital has on things like how much leverage they use. There is the suggestion of a potential risk aversion impact at work, begging the question as to whether simply depositing more money into a trader's account would result in them experiencing better (less bad) returns.

Related to the survivorship issue mentioned in the last section, there exists the potential in using a dataset such as the one analysed here to evaluate the decisions of traders to exit the markets and quit trading. The indication from Figure 3.2 is that by the end of the sample period only about half as many traders were active in the markets as had been the case at its peak. The actual drop-out rate of traders is even worse than 50%, however, as the number of active accounts at the end would have included a number of newer members. Granted, some of those who become inactive may have simply switched to accounts not connected with the social network. Even still, that leaves a large fraction of traders who called it quits. The factors which go into that decision are well worth researching. For example, does being more or less social influence one's decision to stay in the markets longer?

From the social perspective, one of the questions which frequently come up is the motivation of traders in taking part in a social network such as the one studied here. It is a legitimate inquiry which deserves more specific study. Educational, commercial, and social drivers were among those noted from a scan of user profile data, but a much more systematic approach to answering this question is warranted. If nothing else, motivation is a potentially important factor influencing the impact network membership has on a given individual. It could contribute to how active a member is and the type of interactions they are inclined toward, which both factor in to the information exchange aspect of network participation. It also likely directly relates to the question of the potential audience effects which might influence them.

Along those lines, a closer examination of member activity and interaction is warranted. As has been the case with much of the extant research on social networks in finance, this thesis assumes that connectivity leads to information transfer. There is considerable scope to drill down on that matter and examine just how much interaction members have with both friends and non-friends in the network by looking at things like discussion forum chats and instant messaging, as Heimer (2014b) does, perhaps while incorporating demographics. Weighting is a whole other consideration. No doubt certain friends, or types of friends or members, are more influential than others. Being able to establish a sense of how members weight the input they get from their network connections, or the degree to which they are being observed by them, would make for much more meaningful research into the influence of social interaction on trading activity, and by extension returns.

Related to the question of observation is the performance of those traders whose trades are being copied. To what degree does that influence one's trading above and beyond a standard audience effect? The anecdote from the beginning of Chapter 6 would suggest a behaviour effect for at least some traders in being responsible for other traders' returns. Other considerations would need to be ruled out, however.

One final area of specific research potential which is only touched upon in this thesis is that of copy trade provider selection. The process of selecting traders to copy has some commonalities to selecting mutual funds for investment, thus similar techniques could be applied in its analysis. At the same time, the fact that all trades are done in the followers account, thereby allowing them to tamper with active trades, introduces a whole different aspect to things. In particular, the question of the disposition effect comes immediately to mind. This is supported anecdotally by comments made to me by a manager of the social network sourced for the data used here that followers were indeed impairing their performance by closing trades out before their time.

Generally speaking there remains considerable opportunity to extend the literature in the areas of high frequency trading, trading in the foreign exchange market, and in the areas of social networks. All three subjects remain in their relative infancy where the research is concerned

7.4. Final Thoughts

In the realm of active retail trading there is a considerable amount of educational information which is passed around from trader to trader. Some of it has clear links to the findings of behavioural research such as the admonishments “Hold your winners, cut your losers” being related to the disposition effect, and “Don’t overtrade” attempting to curtail overconfident trading. Much of it, however, stands on shakier ground as it has not been subject to rigorous analysis and examination. This thesis is an attempt to at least take a step further along the path academically toward understanding the factors contributing to trading and investing performance and what motivates market participants at the individual level to act as they do.

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